ADVANCED TECHNOLOGY FOR INFILL AND RECOMPLETION CANDIDATE WELL SELECTION

Final Report

Reporting Period Start Date: May 15, 2002
Reporting Period End Date: December 31, 2003

By
Duane A. McVay
Walter B. Ayers, Jr.
Richard Gibson
Jerry L. Jensen

February 2004

DE-FC26-00NT41025
Subcontract No. 2284-TAMU-DOE-1025

Department of Petroleum Engineering
Texas A&M University
3116 TAMU
College Station, Texas 77843-3116

DISCLAIMER

ABSTRACT

The goal of this project was to develop and demonstrate technology for statistical analysis of production and injection data to characterize reservoir performance and assess infill drilling and recompletion potential in stripper oil well fields. Specific objectives of this project were to extend existing statistical methods from single-phase to multiphase, for application to waterflooded stripper oil fields, and to incorporate seismic data to improve both the coverage and accuracy of the statistical reservoir models employed. The improved technology was applied in the South Central Cut Bank Sand Unit (SCCBSU), Cut Bank Field, Montana, to determine enhancement recovery potential and strategies for this stripper well unit.

We investigated three techniques for rapid analysis of production and injection data. Moving window statistical methods are not suitable for analysis of the SCCBSU because the large variation in reservoir properties well-to-well are not consistent with assumptions of these methods. The Albertoni-Lake method indicated the presence of distant injector-producer pairs with strong connectivity, which is consistent with the channelized nature of the reservoir. However, the method does not have a predictive capability. A simulation-based regression approach proved successful in determining locations with significant infill potential in synthetic studies based on the SCCBSU. It was not entirely successful in the analysis of actual SCCBSU data, due to both problems with the production/injection database and limitations in the commercial regression software we employed.

The approximate, simulation-based regression approach described herein can provide a rapid, less-expensive alternative to conventional integrated reservoir studies for determining infill and recompletion potential, and can serve as a valuable reservoir management tool for operators of marginal stripper fields. This approach, as with any method that relies primarily upon well locations and production data, requires a complete and accurate production database for reliable use. We recommend that future research be directed towards continued development of the simulation-based regression approach, and recommend that it be validated in stripper gas reservoirs prior to further application in stripper oil reservoirs.

Table of Contents:

LIST OF TABLES

LIST OF FIGURES (Located at end of report)

EXECUTIVE SUMMARY

In this project we used statistical analysis of production data to characterize reservoir performance and to select locations for infill drilling or recompletion in stripper well fields. Integrated geological and reservoir engineering studies provide the best source of information for making reservoir management decisions. However, these studies are prohibitively time-consuming and expensive for many marginal stripper fields. Past studies have demonstrated that methods involving statistical analysis of readily available well location and production data, although less accurate than integrated studies, can be useful reservoir management tools in marginal reservoirs.

A specific objective of this project was to extend the existing Mosaic moving window statistical method, which has been used primarily in unconventional gas reservoirs, from single-phase to multiphase capability for application to waterflooded stripper well fields. A second objective was to incorporate seismic data to improve both the coverage and accuracy of the statistical reservoir models employed. The improved technology was to be applied in the South Central Cut Bank Sand Unit (SCCBSU), Cut Bank Field, Montana, to determine enhancement potential and strategies for this stripper well unit.

To incorporate seismic data into the statistical analyses, we evaluated seismic attributes and well log porosities in the Lower Cut Bank sand to establish a correlation and to model the porosity distribution. The three seismic amplitude attributes extracted from the Cut Bank interval were maximum amplitude, mean amplitude, and root-mean-squared (rms) amplitude. The correlation between porosity and both mean amplitude and rms amplitude are poor. On the other hand, we found that the maximum amplitude varies inversely with porosity of the Cut Bank reservoir, with a correlation coefficient of 0.51. Good correlation between seismic amplitude and log porosity enables the use of seismic data to map porosity trends for use in production data analysis.

Since statistical methods rely primarily on well locations and production and injection data, it is critical to have a complete and accurate database if the results of the statistical analyses are to be useful and reliable. Locating, quality checking and organizing the production and injection data for the 70+ year history of the SCCBSU proved to be difficult and time-consuming. Despite considerable effort over a year's time, the database is still incomplete, due primarily to data loss because field operations changed hands over the unit's history. Production data exist by tract only for the first 30 years of unit history. Critically, only unit-wide production figures are available for the period from approximately 1960 to 1980. Lack of a complete production and injection database limits the effectiveness of statistical methods to reliably determine infill and recompletion potential in the Cut Bank field.

We attempted a Mosaic interpretation of the SCCBSU production and injection data. However, we did not observe good correlation between production indicators and geological trends, due in part to problems with the production and injection database. In addition, we determined that the Mosaic method is not suitable for analysis of the SCCBSU because the large variation in reservoir properties well-to-well are not consistent with a major assumption of the Mosaic technique, namely that reservoir properties are relatively uniform in local windows of 5 to 20 wells.

Therefore, we employed a second technique, the Albertoni-Lake (AL) method, to interpret the production-injection performance of wells in the Lower Cut Bank reservoir of the SCCBSU. The technique, which uses only production and injection rate data, uses a constrained multivariate linear regression analysis to provide information about permeability trends and the presence of transmissibility barriers. The method indicated the presence of distant injector-producer pairs with strong connectivity, which is consistent with the channelized nature of the reservoir. Unfortunately, the method does not have a predictive capability. Thus, while we might be able to qualitatively infer potential infill well locations, the method does not provide a means of quantitatively assessing potential infill incremental recovery.

Next, we employed a third method, a simulation-based regression approach that we have developed for application in unconventional gas reservoirs. The approach uses reservoir simulation with automatic history matching to invert production and injection data to determine the permeability distribution. The reservoir simulation model and the resultant permeability distribution are used in an automated procedure to determine quantitatively the infill potential throughout the reservoir. The method differs from conventional reservoir simulation studies in several respects; the greatest difference is that we use only readily available data in constructing the simulation data set. Using an approximate data set results in similar time and cost requirements as for a Mosaic statistical analysis. The results are also necessarily approximate, but tests in other studies have demonstrated that, because we are using a simulator as the reservoir model, the results are more accurate than those from Mosaic.

We tested the simulation-based regression approach in several synthetic cases derived from the SCCBSU. The method was successful in recovering the approximate permeability distribution and determining locations in the unit with significant infill potential. Locations with infill potential correlated with geological trends; the greatest potential existed in incompletely swept channel deposits. Analysis of actual SCCBSU production and injection data was not completely successful, due both to problems with the production and injection database and limitations in the commercial automatic history matching software that we used. While we were able to map infill potential for the SCCBSU, the estimates possess considerable uncertainty and further study is required to verify their reliability.

Based on our research, we conclude that the simulation-based regression approach is superior to Mosaic for rapid assessment of infill potential, and that it can be a valuable reservoir management tool for operators of marginal stripper fields. However, this approach, as with any statistical method that relies primarily upon well locations and production data, requires a complete and accurate production database for reliable use. We recommend that future research be directed towards continued development of the simulation-based regression approach, with a focus on fit-for-purpose regression technology. We recommend that the approach be further validated in stripper gas reservoirs prior to additional application in stripper oil reservoirs.

INTRODUCTION

Quantifying the remaining potential in marginal oil and gas fields and basins is usually difficult, due to (1) high vertical and lateral variability in rock quality and connectivity; (2) variable completion and stimulation practices; (3) inconsistent well spacing; and (4) inadequate databases for reservoir characterization. The most accurate assessment of performance enhancement potential in such fields is a detailed, integrated reservoir evaluation using geophysical, geological and engineering data and interpretations. This requires compiling a detailed database, developing a geological model, estimating distributions of static reservoir properties such as porosity and permeability, constructing and calibrating a simulation model, and finally, using the model to predict and optimize performance.

Unfortunately, integrated studies are prohibitively time-consuming and expensive for stripper oil and gas fields, and they are impractical for independents with limited staff. In addition, there are often insufficient data for these studies. Hence, there is a need for less-demanding methods that characterize and predict heterogeneity and production variability. As an alternative approach to conducting detailed studies, various authors have used empirical or statistical analyses to model variable well performance (Voneiff and Cipolla, 1996; Reese, 1996; Hudson *et al.*, 2001; and Guan *et al.*, 2002). Most are based solely on well location, production and time data. Mosaic Technology[5] is an advanced technique that uses a model-based 4D regression of production *vs.* virgin productivity, cumulative production, and well spacing. A field is evaluated not as one single study, but as a mosaic of overlapping local studies. This technique can qualitatively indicate the degree of reservoir heterogeneity, pinpointing areas with rework or infill potential.

The statistical methods for production data analysis mentioned above have been developed primarily for depletion processes in gas reservoirs. In this project, researchers from Texas A&M University and MGV Energy endeavored to develop improved technology for rapidly assessing infill and recompletion potential in marginal oil fields. This requires extending the technology to include multiphase displacement processes, to allow application to waterflooding projects, where many stripper oil wells occur. Since Mosaic and other moving window methods are based primarily on analysis of production data, they can predict infill potential at only those locations near existing wells. Thus, another goal of the project was to enhance the statistical methods by incorporating seismic data, which has significant potential due to its large coverage and because such data can be related to interwell reservoir properties.

In conjunction with an operating company, Quicksilver Resources, we sought to demonstrate the utility of enhanced production data analysis in stripper oil and gas fields by applying the enhanced procedures in South Central Cut Bank Sand Unit (SCCBSU) of Cut Bank Field, Montana. Much of this unit has been waterflooded and most active wells produce less than 5 STB/D. A primary objective of the project was to determine the infill or recompletion potential for this unit.

OBJECTIVES

The specific project objectives were to:

- extend existing statistical methods from single-phase to multiphase for application to waterflooded stripper well fields;
- incorporate seismic data to improve both the coverage and accuracy of the statistical reservoir models employed; and
- apply the developed method to characterize reservoir performance, select locations for infill drilling, and target wells for reservoir recompletion in the Cut Bank stripper well field.

FIELD OVERVIEW

Cut Bank field, located in Glacier, Pondera, and Toole Counties, northwest Montana **(Fig. 1a),** was discovered in 1931. Cut Bank oil field is a long, narrow oil-leg on the west side of a larger stratigraphic trap on the west flank of the Kevin-Sunburst Dome. Production in the Cut Bank field is primarily from the Lower Cretaceous Cut Bank Sand, which is a fluvial sandstone deposit **(Fig. 1b and Fig. 2).** The oil field is 30 miles long and ranges in width from less than 2 miles near the northern end to about 6 miles near the southern end. The gas-oil contact of the Cut Bank sandstone is at approximately +1,040 ft.. At the north margin of the field, the Cut Bank oil/water contact is tilted, cutting across structural contours from +1,300 to +600 ft from the west to northeast **(Fig. 3).**

The Cut Bank Sand is the most important producing unit in the Cut Bank oil field. It is a braided-to-meandering fluvial sandstone deposit (Shelton, 1969; Weimer, 1982; Berkhouse, 1985; Horkowitz, 1987; and Hopkins, 1993) that varies in thickness and pinches out against the Ellis Group on the east, forming a stratigraphic trap. The Cut Bank Sand is comprised of upward fining sands with interbedded shales. Thickness of the unit ranges from to more than 80 ft on the west to zero at the pinchout on the east. Cut Bank sandstones are generally medium- to coarse-grained litharenites in which the lithic component comprises a wide range of chert and silicified sedimentary rock fragments. On the basis of outcrop studies, Horkowitz (1987) described the principal detrital constituents of the Cut Bank sandstone as quartz, silicified carbonate clasts, and argillaceous chert clasts **(Fig. 4).** Chert content of the sandstone may exceed 50%. Texture ranges from conglomerate to fine-grained sand, and porosity and permeability vary appreciably, both laterally and vertically. The highest porosity and permeability occur in medium-grained, conglomerate-free, cherty sand (Cupps, 1967). Because of wide variation in porosity and other reservoir properties, oil saturation is very irregular.

The Cut Bank Sand is composed of two members, the Upper and Lower Cut Bank Sand (Fig. 2). The boundary between the upper and lower sands varies from gradational to abrupt. The lower sand is the main producing horizon. It generally has the characteristics of a blanket sand that averages approximately 17 ft thick. The average porosity of the pay section is 14%, and permeability ranges from 10 md to 1,500 md, with the average being approximately 50 md (Matthies, 1962).

The Upper Cut Bank sand is thinner and not as wide spread as the lower sand, and it produces only locally. Interpretation of the Upper Cut Bank sandstone is based mainly on log analysis. It is composed of fairly clean, uniform, fine- to medium-grained sand (Hill, 1989). Unlike the Lower Cut Bank Sand, a basal conglomerate is rare, and when it is present it is quite thin.

The South Central Cut Bank Sand Unit (SCCBSU), focus of this study, produces oil from Cut Bank sands at an average depth of 2,850 ft, or +900 ft elevation above mean sea level **(Fig. 5).** Primary production and waterflood projects have yielded approximately 43 million bbls of the 126 million bbls of oil originally in place (OOIP) in the complex, heterogeneous reservoirs. Of the OOIP, 18.5 % was recovered by primary means. The SCCBSU water flood program was started in May 1963 and is still operating and expanding **(Fig. 6).** Daily production has declined to less than 5 STB/day in most active wells. Secondary recovery accounts for an additional 5% of the OOIP. At present, there are 277 wells in the SCCBSU area, of which 55 are active producers, 29 are active injectors, and 194 wells are idle. The current average well spacing is 92 acres/well.

Hardy and Treckman (1996) identified a 2-4 ft thick bentonite named the "Tin Roof" at the base of the Moulton (top of Sunburst) (Fig. 2). This layer is absent over part of the Cut Bank Unit area, where a major incised valley is present **(Fig. 7).** The incised valley is 1 to 1.5 mi wide and is at least 150 ft deep. The valley fill creates stratigraphic trapping potential in the Sunburst and, possibly, in upper Cut Bank sands.

In 1998, a 3-D seismic survey was acquired over an 8-mi^2 area of Cut Bank field to improve the ongoing waterflood program. The 3-D seismic data indicated that reservoir compartmentalization is controlled by lateral and vertical facies changes, not by faults or tectonic features (DeAngelo and Hardage, 2001). Major (and some smaller) channel-fill sandstones were delineated. According to DeAngelo and Hardage (2001) the "Tin Roof" bentonite, where present, appears to dampen the seismic reflectors below it, resulting in reduced seismic clarity of the lower Cut Bank sand. QRI drilled 5 new wells on the basis of the seismic interpretation. These new wells experienced oil production rates and watercuts similar to existing wells in the field.

DATABASE

The reservoir seismic database covers an 8-mi^2 region of the Cut Bank field. The well log database includes 275 wells located in the SCCBSU, NCCBSU, NWCBSU and TRIBAL units of Cut Bank field. The geophysical log suite varies among wells; log suites available in the database are combinations of gamma ray, density porosity, neutron porosity and other curves, such as old gamma ray neutron, resistivity, and spontaneous potential. In addition, core analyses are available for 11 wells. Upon reviewing the content and quality of data files, we concluded that the available velocity data were insufficient for the intended analysis. Therefore, we obtained additional well logs from

Riley Electric Log Inc., and Quicksilver Resources had them digitized. Production history data are available for 194 wells, not including injection wells and wells with only water production data.

RESULTS AND DISCUSSION

RESERVOIR CHARACTERIZATION

The primary objective of this project was to develop statistical methods for analyzing production and injection data for rapid assessment of infill potential in marginal oil reservoirs for which a complete integrated reservoir study cannot be afforded. It was necessary to conduct a reservoir characterization study in this study, however, to provide a basis for validation of the statistical methods. Another objective was to extend existing statistical methods to incorporate seismic data. This required the integration of seismic and petrophysical data, which we describe below.

Facies Analysis

Commonly, fluvial reservoirs are highly heterogeneous, with barriers or baffles to fluid flow within sand bodies that can be simple or highly complex in terms of three-dimensional geometries. Therefore, it is critical that a full assessment of internal sedimentary structures and hierarchies is determined and that potential compartments are well defined. Integration of geologic and engineering data can be used to identify reservoir heterogeneities responsible for entrapment of bypassed oil.

Integrating geologic and engineering data to identify heterogeneities in the subsurface involves several key steps, including:

(1) determination of reservoir architecture;

(2) investigation of the trends in reservoir fluid flow; and

(3) integration of fluid flow-trends with reservoir architecture.

To accomplish these steps, we evaluated maps (gross sandstone, log facies, percent sandstone, and porosity) and cross sections to establish a reliable reservoir stratigraphic model and to clarify reservoir architecture. Two maps, gross sandstone and net thickness, were provided by Quicksilver Resources; the remainder were produced in this project.

We began by refining the interpretation of the Cut Bank Sand base and top in well logs obtained from Quicksilver Resources and Internet Resources (Montana Oil and Gas Commission). The basal Cut Bank Sand contact is sharp in all the wells, but identifying the upper boundary is challenging. We used gamma ray (GR) character to produce a log-pattern (electrofacies) facies map of the more continuous Lower Cut Bank Sandstone member. Cut Bank Sand log patterns are blocky in the mid-channel deposits and upward fining or serrated at the channel margins. In the interchannel, floodplains areas, the thickness decreases markedly and the log patterns are serrated or sometimes upward-fining.

Overlaying the GR logs on a gross sand thickness map allows assessment of the reservoir architecture - geometry, size, vertical contacts, bedding characteristics, and thickness. We also used this technique to map porosity distributions in the Lower Cut Bank Sandstone throughout the SCCBSU area.

Porosity

One aim of this project was to demonstrate the value of seismic data for predicting hydrocarbon production. Seismic-based porosity predictions are one way to incorporate the seismic data into a relevant reservoir model. Some data analysis is required, however, before seismic-determined porosities can be calculated. In particular, seismic attributes and well log porosities must be compared to demonstrate any relationships and to model the porosity distribution throughout the field. Normally, both seismic attributes and log properties are averaged for a stratigraphic interval. The objective is to have a pair of attributes and log properties values for each well that intersects the layer so that relationships between these quantities can be determined. Therefore, it is important to construct a representative model of reservoir porosity from well logs.

Core data were used to calibrate and refine the interpretation from well logs. The available core porosity data were cross-plotted with log-derived porosity on a well-by-well basis. Most of the wells in the Cut Bank field have a density porosity curve. Core data are available from 6 wells located in the northern part of seismic survey. There are core data from a few other wells that we could not use for calibration because of the absence of density logs in these wells. **Table 1** summarizes the results of correlating core and density porosity data for the wells that have both types of data. To reduce the degree of scatter, a running average was applied to the core porosities. Core porosity curves were depth shifted to match with log depths using the gamma-ray curves.

Table 1. Summary of core porosity and density porosity calibration through cross-plotting.

Well #	Core data interval, ft	Available log curves	Depth shift, ft, (- downward, + upward)	Correl. Coef. - R	Relationship between core porosity and density porosity
37-7	2825-2855	GR, CALI, SP, Resistivity, Neutron Porosity, Density Porosity	3	0.9581	Core por=0.060712+0.508972*Density por
33-5	2830-2855	GR, Density Porosity	1	0.687675	Core por=0.090729+0.411721*Density por
19B-3X	2782-2808	GR, Density Porosity	-1.5	0.778207	Core por=0.041697+0.797283*Density por
39-1X	2923-2942	GR, Density Porosity	-3	0.070561	Core por=0.037309+0.879690*Density por
36-5	2932-2957	GR, Density Porosity	-2	0.748487	Core por=0.024393+0.82846*Density por
22-6	2784-2805	GR, Density Porosity	-3	0.796005	Core por=0.041014+0.658383*Density por

The results **(**Table 1**)** show that the correlation coefficient is low in all the wells except Well 37-7 **(Fig. 8).** When we applied the relationship between core porosity and density porosity from that well to other wells, it gave net pay average porosities of approximately 11 pu (porosity units). This value is 3 pu lower than the reported field net pay average porosity value from literature and reports supplied by Quicksilver Resources. In previous studies, net pay was defined based on a 10% porosity cutoff. We evaluated the appropriateness of a 10% porosity cutoff by cross plotting the available porosity and permeability data from 13 core reports from the Cut Bank field. There is a rather strong change in the behavior of the data, between data below and those above the 10% porosity line **(Fig. 9).**

In an ideal case, there should be a one-to-one relationship between core porosity and density porosity. **Fig. 10** shows the averaged core porosity vs. density porosity plot for all the wells that have core data. Wells 36-5 and 37-7 fall near the line, indicating good correlation. However, in Wells 33-5 and 39-1X, core porosity is consistently higher than density porosity. Based on core report summaries, cores from these two wells include abundant heavy minerals. This may also be the reason for poor agreement for wells 19B-3X, 36-1, and 22-6, where the log porosity underestimates the core-derived value. We conclude that the presence of heavy minerals causes the density log to be an unreliable porosity predictor.

Because the density log does not appear to give reliable porosity estimates, we examined porosity in wells that also had a neutron log. The combination of density and neutron logs gives porosity estimates that are less sensitive to lithologic variations than does the density porosity alone. There are 21 wells in the SCCBSU area that include both density and neutron porosity logs. The neutron-density average porosity (PHIA) value is close to the field-wide average (14%) reported in literature and reports **(Fig. 11).** Therefore, we decided to use PHIA values for the log porosity-to-seismic porosity calibration.

Integration of Seismic and Well Log Data

The critical step in seismic-guided log-property mapping is having accurate time-to-depth relationships. We estimated velocities from density logs using the Gardner equation ($\rho=cV^{\alpha}$, where α=0.21 and c=0.35). The Gardner equation parameters (α and c) were estimated by combining data from 4 wells that have density logs and either sonic log or a borehole seismic report available.

Seismic velocity estimates determined from VSP data are available for one well (Well 54-8) in the study area, and this allows a check of depth-time relationships determined from log data alone. The two approaches compared favorably in the southwest area, but in the northeast part of the seismic survey area, the VSP data produced a significantly different depth-time relationship. Specifically, the difference between the estimated two-way traveltime at the relevant Cut Bank formation was of about 25 msec.

Thus, to tie seismic and well data, we used VSP (Well 54-8) data for the south and southwest parts of the seismic survey area. Sonic data derived from the density (Well 37-7) were used for the northeast area.

We generated synthetic seismograms using the standard convolutional model that convolves an estimated wavelet and a reflection coefficient series. The latter was calculated from impedance contrasts determined from sonic and density log. The objective is to correlate the reflections that we expect the formations to create (the synthetic) to the reflections in the seismic data. The seismic can then be interpreted accurately and compared directly to log measurements.

We integrated seismic and well log data in the Cut Bank field to determine which, if any, seismic attributes can be used to map reservoir properties and can be incorporated into production-based statistical analysis. The variations observed in seismic attributes such as amplitude should be a function of variations in reservoir parameters, including porosity. To test this hypothesis in the Cut Bank field, we compared seismic attributes with well log porosities to establish a correlation and to model the porosity distribution throughout the field.

By plotting the average Cut Bank sandstone porosity at each well against the seismic amplitude at that well, the nature and strength of the relation was investigated. We used average neutron-density porosity (PHIA) values for the log porosity from 21 wells.

The three seismic amplitude attributes extracted from the Cut Bank interval were maximum amplitude, mean amplitude, and root-mean-squared (rms) amplitude. The correlation between porosity and both mean amplitude and rms amplitude are poor. On the other hand, we found that the maximum amplitude varies inversely with porosity of the Cut Bank reservoir **(Fig. 12).** The regression had a value of $R^2 = 0.51$ when fitting the maximum amplitude to the average porosity of net pay (PHIA > 10%). Two points, wells 49-10 and 39-4 (polygons in **Figs. 12 and 13**), were excluded in obtaining this relationship. This reasonably good correlation between seismic amplitude and log porosity enables the use of seismic data to map porosity trends for use in production data analysis.

The maximum amplitude at the Well 49-10, located at the center of the seismic survey area, is anomalously high compared to the average log porosity (PHIA). This high value may result from an inconsistent interpretation of the base of the Lower Cut Bank strata (Ellis top) in this area. This horizon is at the zero crossing above positive amplitudes (peaks) throughout all of the seismic survey **(Fig. 14),** with the exception of the problem area of Well 49-10 **(Fig. 15).** Another cause may be the location of this well adjacent to the western edge of the Lower Cretaceous Gorge. Well 39-4 is also located near the western edge of the Lower Cretaceous Gorge. In this well the maximum amplitude value again under-predicts the porosity. Here, also, another explanation may be an inconsistency in the interpretation and stratigraphic ties of the Lower Cut Bank interval in well log and seismic data **(Fig. 16).**

Evaluation of Geological Maps

Net-thickness maps of lower Cut Bank sand in the SCCBSU area were prepared separately by Unocal, the prior operator of the field, and the QRI/BEG (Quicksilver Resources/Bureau of Economic Geology) team. The QRI/BEG thickness map incorporated both seismic amplitude data and well log data. By superposing the QRI/BEG net sand thickness map on the seismic average absolute amplitude map, we found that regions interpreted as higher average absolute amplitude correspond to higher estimated net sand thickness, suggesting that QRI/BEG mapping was guided by seismic amplitude occurrences and trends **(Fig. 17).** However, we found that there is no correlation between the measured net sand thickness from the well logs (based on 60% GR and 10% porosity cutoffs) and the average absolute amplitude values **(Fig. 18).** Therefore, we infer that there are limits on the accuracy of the QRI/BEG interpretation. Also, there are significant differences between the QRI/BEG average absolute amplitude map and the earlier UNOCAL net sand thickness map **(Fig. 19).**

Interpretation of net sand thickness in the area of Well 33-1 differs greatly on the UNOCAL and QRI/BEG maps (Figs. 17 and 19). Production data for the SCCBSU 33-1 record a rapid increase in oil production in response to waterflooding. Currently there are no logs available for this well, precluding any direct determination of sand thickness to assess which map is more accurate.

However, we used results of the QRI 1999 five-well drilling program to compare UNOCAL's and QRI/BEG's net sand thickness maps to the Cut Bank thicknesses encountered in wells **(Table 2).** In Wells 49-14, 38-13, and 37-7, there is large disagreement among the net sand thickness values from three different sources (UNOCAL map, QRI/BEG map and actual, from well logs), which demonstrates the uncertainty associated with indirect methods of thickness determination and reservoir mapping.

Table 2. Comparison of mapped and actual net sand thicknesses from QRI's 1999 five-well drilling program.

Well (SCCBSU)	Unocal Mapped H (ft)	QRI/BEG Mapped H (ft)	Actual H (ft) (from new well logs)
49-14	6	20+	0
38-13	6	20+	23
54-10	15+	30+	16
37-7	6	25+	26
47-7	25+	30+	34

Seismic and well-log cross sections (W-to-E) **(Figs. 20 and 21)** were made through the SCCBSU 49-14 well location, where there was a large error in predicted thickness. The objective was to determine why the QRI/BEG mapping predicted so much sand in an area where no sand was present. As mentioned, a high average absolute amplitude was found to correspond to high net sand thickness values on the QRI/BEG net sand thickness map in all locations, except that of Well 49-14. At this well, the seismic amplitude is anomalously high and does not match expected thickness values. Moreover, this well is near Well 49-10, where the maximum amplitude is anomalously high compared to the average log porosity (PHIA), as was discussed earlier (Fig. 12). We conclude that this high porosity value may result from an inconsistent seismic pick of the base of the Lower Cut Bank strata (Ellis top) in this area, owing to locally complex seismic responses.

PRODUCTION AND INJECTION DATA ANALYSIS

The primary objectives of this project were to (1) extend an existing statistical analysis technique, the Mosaic moving window method, which had been developed for gas reservoirs, so it could be used to rapidly assess infill potential in stripper oil fields and (2) demonstrate its utility by applying it in South Central Cut Bank Unit. In the course of our investigation, we discovered limitations in applicability of the Mosaic method to the Cut Bank field, discussed below. Thus, we investigated the use of two alternative methods, the Albertoni and Lake (2003) method and a simulation-based inversion method. The most important data, and in some cases the only data, required for each of these methods are well locations and production and injection data. In the sections that follow we first discuss the assembly of the well and production/injection database. We then discuss application of each of the three methods to the Cut Bank field.

Production and Injection Database

1. Database creation:

   Locating, quality checking and organizing the production and injection data for the SCCBSU proved to be much more difficult than anticipated. The unit has a long history (beginning in the 1930's), and operations have changed hands over the years, resulting in data loss. Data had to be acquired from multiple sources, and for some years, entered by hand from paper records. Quicksilver designed an Access database specifically for the SCCBSU, and began loading the production and injection data shortly after project initiation. Problems associated with locating and reconciling data slowed database completion and project progress significantly; the final database used for the project was not completed until over a year after project initiation.

   Although we have loaded all production and injection that we were able to locate, the database is far from as complete as we would like. There are no significant amounts of recorded gas production data. The database contains individual-well injection data for the entire waterflood period. However, it contains individual-well production data only from the early 1980's forward. Early production data from inception of the field in 1932 to approximately 1960 exists by tract (or lease) rather than by individual well. Between about 1960 and the early 1980's, the detail, quantity and quality of production data are variable, ranging from unit-wide information only during the 1960's to sporadic and incomplete individual-well production data during the 1970's. Individual-well data becomes more reliable during and after the 1980's, when Montana's oil and gas regulatory agency began requiring the reporting of individual-well production volumes. Still, these individual-well volumes are based on allocation of gathering center volumes using periodic well production tests.

Lack of a complete production and injection database will limit the effectiveness of statistical methods to reliably determine infill and recompletion potential in the Cut Bank field, since these statistical methods rely primarily on interpretation of individual-well production and injection data.

2. Well types:

   There are approximately 370 wells and 13 operators in the SCCBSU unit. The largest operator, Quicksilver Resources, Inc., operates 78.3% of the SCCBSU wells. **Table 3** shows information on well types. About 62% of the wells are oil production wells and 34% are injection wells.

Table 3 – Well Types in SCCBSU

Well Type	Number of Wells	Percentage, %
Dry Hole	7	1.90
Gas	3	0.82
Injection, EOR	126	34.24
Injection, Indian Lands	1	0.27
Oil	228	61.96
Total: 5 well types	**369 wells**	**100 %**

3. Waterflooding history:

   A pilot waterflood in the Cut Bank Sand reservoir was started in 1952 in the center of a unitized 640-acre tract. The first phase of waterflood development began in the late-1950's or early 1960's, and was completed in 1962 using a five-spot injection pattern on several tracts in the southern part of the field. Waterflood area expansion projects were completed in 1966, 1969, 1970, 1976, 1981, 1983, 1984, and 1988.

4. Production and injection data review:

   An examination of the production and injection data reveals that fluid injection far exceeded fluid production from 1970 to 2002 **(Fig. 22).** The fluid production from January 1970 to July 1972 is very small because of gaps in the production database during that time. **Fig. 23** shows the correlation between fluid injection and fluid production for SCCBSU. Although a trend is apparent, the data do not correlate well (R^2 is 0.27). **Fig. 24** shows the relationship between water injection and oil production over the period 1970 to 2000. Correlation between field water injection and oil production is only marginal, and the water injection far exceeds the oil production. At this time we cannot explain why the fluid injection greatly exceeds the fluid production, although we are investigating the cause. Inability to explain and account for this phenomenon may limit the effectiveness of the Mosaic statistical analysis.

Based on Figs. 22-24, it does not appear that waterflooding has been particularly effective in the South Central Cut Bank Unit. However, there are instances of apparently significant waterflood response for selected wells **(Figs. 25 and 26)**.

The Mosaic Technique

The Mosaic technique was originally developed by MGV Energy Inc. for determination of infill potential in unconventional gas reservoirs. The technique is an extension of the method described by Voneiff and Cipolla (1996), and is described in Guan *et al.* (2002). It consists of a multitude of local analyses, each in an areal window centered around an existing well. Unlike the method of Voneiff and Cipolla, however, the Mosaic technique employs a more rigorous, model-based analysis in each moving window. The model is based on a combination of the material balance equation and the pseudosteady state flow equation, simplified by assuming that many properties are constant within an individual window. The result is a linear, multivariate (4D) regression equation that is applied within each window:

$$BY = f(VBY, G_p/A, A)$$

where

BY = best year, the best 12 consecutive months of production divided by 12. BY has been demonstrated to correlate well with long-term production (Voneiff and Cipolla, 1996). BY is used as a proxy for production rate in the pseudosteady state flow equation.

VBY = virgin best year, the BY of a well at virgin conditions. Depletion effects are removed by computing the BY of a local area at a time before depletion using a 2D regression of BY *vs.* well start date. VBY is used as a proxy for *kh* in the pseudosteady state flow equation.

Gp/A = cumulative production divided by well spacing.

A = Well spacing, area of Voronoi polygon around each well based on well locations. Used as a proxy for drainage area in the pseudosteady state flow equation and material balance equation.

Regression coefficients for each window are determined by regressing these parameters for the wells within each window. The windows are limited in size, e.g., 3000 acres, and generally contain 5 to 20 wells. If the number of wells in a window is less than a minimum value, e.g., 3-5, a regional or global regression is used instead of a local regression.

Once the regression equation coefficients are determined for each window, performance can be estimated for infill wells by substituting the appropriate values for candidate infill well conditions (well spacing, G_p/A, VBY). The result of this analysis is a prediction of BY for a new infill well offsetting each existing well. Results are approximate, due to the assumptions inherent in the procedure, although still useful. As reported by Guan *et al.* (2002), Mosaic analysis can reliably determine the infill potential for groups of wells, often to within 10%. However, individual well predictions can be off by 30% to 50% in some cases. When geological data are available, there is often agreement between geological features and trends in production indicators predicted by the Mosaic analysis.

The primary advantages of the moving window technique are its speed and its reliance upon only well location and production data. It is routinely used to conduct infill screening studies of projects consisting of 1000's of wells and can be used to evaluate an entire basin in a few man-days.

Since the Mosaic technique was designed for unconventional gas reservoirs, one of our objectives was to incorporate multiphase flow capability so the technique could be applied to waterflooded stripper oil fields. Since the Mosaic correlation equation does not include a term related to pore volume, another objective was to provide for the incorporation of other types of data, such as seismic data, that can serve as a proxy for porosity or porosity-thickness in the multidimensional regression.

Our first step was to change all the queries and spreadsheets of the Mosaic software from single-phase gas to single-phase oil. There are 10 spreadsheets and about 40 queries in the Mosaic software. We then began a preliminary Mosaic analysis of the SCCBSU production data.

Production Trends Analysis

Standard practice in Mosaic studies is integration of production trends with reservoir architecture and properties to help in understanding reservoir performance. Correlation of production with location helps to establish the sensitivity of production to geological features. This correlation was attempted in SCCBSU by comparing Lower Cut Bank Sandstone production performance maps with geologic and reservoir-quality maps, such as gross thickness, structure, net thickness, net-to-gross ratio and average porosity.

Production indicator maps, made on a well-by-well and a tract-by-tract basis, were used to establish production trends in the Lower Cut Bank sand in the SCCBSU. Well-by-well production data after 1972 were used to generate several typical Mosaic production indicator maps including:

- best year of oil production (best consecutive 12 months production divided by 12);
- virgin best year (best year of the well corrected for the effects of depletion);
- infill best year (calculated best year for an infill wells offsetting each well); and
- cumulative production, by well.

Tract-by-tract production data cover the periods from 1932 to 1966 and from 1972 to 2000. Indicator maps made from these data included:

- best year production (best consecutive 12 months production divided by 12);
- production/tract area (STB per acre);
- cumulative oil production;
- cumulative gas production;
- cumulative water production;

- cumulative water injection; and
- difference between injected water and total produced liquid (oil and water).

We attempted to correlate the areas of good and poor production response to features on the geological maps. In general, we did not observe good correlation. Interpretation was hindered by disagreement between geological maps obtained from two different sources and by problems with production and injection data, both discussed previously, and by the general character of reservoir property distributions in the Cut Bank sand. There are two primary issues related to production and injection data. First, there is a significant amount of missing individual-well production data, which is required for the Mosaic technique. We have about 30 years with only data by tract and about 20 years with only data by unit. In addition, there is an unreasonably high ratio of cumulative water injected to liquid (oil and water) produced. We have some concern that a significant amount of injection may have gone out of zone; however, this is difficult to confirm. Out-of-zone injection could significantly affect the accuracy of our interpretations and predictions.

Finally, we observed significant variation in reservoir properties well to well, such as net sand thickness (Figs. 17 and 19), due to the channelized nature of deposition in the Cut Bank sand. This violates one of the major assumptions of the Mosaic technique, namely that reservoir properties are relatively uniform in windows of 5 to 20 wells. Because of all these complications, particularly the latter, we concluded that further Mosaic analysis of the Cut Bank sand would most likely be unproductive. Therefore, we investigated two alternate techniques for statistical analysis of production and injection data.

The Albertoni-Lake Technique

We employed a new technique developed to quantify communication between wells to interpret the production-injection performance of wells in the Lower Cut Bank reservoir of the South Central Cut Bank Unit. The technique, which uses only production and injection rate data, uses a constrained multivariate linear regression analysis to provide information about permeability trends and the presence of transmissibility barriers (Albertoni and Lake, 2003). The Albertoni-Lake (AL) technique calculates the fraction of flow (λ) in a producer attributable to flow at an injector. The analysis is performed on a field-wide or regional basis and analyzes multiple well influences in a single step. It uses filters to account for the time lag and attenuation occurring between each injector-producer pair.

We subdivided the field into three study regions, namely, the north, north-central, and south regions and applied the AL method separately to each region. We considered only those periods in which the greatest number of producers and injectors were active with minimum breaks in production and/or injection at each well. The active wells were then further screened to 16 producers and 25 injectors using the criteria of highest rates and fewest rate disruptions.

The program calculates the λ's for each of the 400 injector-producer pairs in a region. The λ's calculated by the program are essentially vector quantities whose magnitudes and directions can be represented in an arrow plot (**Fig. 27**). The magnitude of λ is represented by the arrow length. The arrow points from the injection well towards the producer for which the λ is calculated.

Production Trends Analysis

Figs. 28-30 are the arrow plots overlain on the BEG-Quicksilver net-sand thickness map of the field for each region. There is a generally good correspondence between the calculated λ and the presence of net pay as indicated on the map; there are red or green colored regions between wells where λ is large and more blue where λ is small. The variability of the arrow lengths with direction suggests the connectivity is strongly anisotropic, favoring the orientations of the channel axes. The presence of distant injector-producer pairs with strong connectivity (e.g., Fig. 28) appears to reflect the channelized nature of the reservoir.

Figs. 28-30 show the more recent version of the net pay map, which was produced by Quicksilver Resources and the Bureau of Economic Geology (QRI/BEG). An older net pay map produced by Unocal, which shows the fluvial channels as more distinct, separated events **(Fig. 31),** shows a poorer comparison between net pay and the injector-producer connectivities. This suggests that the older map may be less accurate.

Further analysis of the λ's was performed to confirm their interpretation as a measure of connectivity, since the favorable comparison with the QRI/BEG map was subjective. We tested the relation of the λ's to oil production, for each producer in each region. In all three regions, there appears to be a proportionality between the maximum λ and the cumulative oil produced, N_p, (**Figs. 32-34**). This again suggests that the λ's are indeed measuring connectivity. However, this analysis is incomplete because it does not take injection rate into account.

Finally, we evaluated several production wells to determine if the weighted injection did, indeed, match the production profile. **Figs. 35 and 36** show typical results observed. First, there is a good match between the actual production of total fluids (blue diamonds) and the weighted sum of injector contributions (pink squares). Second, a significant mismatch occurs (blue triangles) when one of the injectors is excluded. This suggests, again, that the λ's are measuring interwell connectivity.

The AL method indicates that injector—producer influence reflects the channelized, elongate geometry of the reservoir. This gives rise to significant long-distance influence exerted by some injectors on producers. Such long-distance connections are incompatible with the assumption of using Mosaic and other, moving window methods. These methods require significant production influences to arise only from nearby wells. While the AL method does appear to be able to detect long-distance connectivity, unfortunately it does not have a predictive capability. Thus, while we might be able to qualitatively infer potential infill well locations, the method does not provide a means of quantitatively assessing potential infill incremental recovery. An alternative approach to both Mosaic and the Albertoni-Lake method is needed to fully assess infill potential in reservoirs such as the Cut Bank Sandstone.

Simulation-Based Regression Approach

As an alternative to Mosaic and other moving window methods, we have been investigating in other research projects the use of reservoir simulation combined with automatic history matching to rapidly assess infill-drilling potential in unconventional gas reservoirs. As described above, the Mosaic method combines the material balance equation with the pseudosteady state flow equation in a 4D regression of production data within each moving window. A reservoir simulator also combines material balance equations with flow equations, albeit with more rigor. Our approach is to use reservoir simulation combined with automatic history matching to regress production data, similar to the Mosaic approach. The difference is that we regress, or invert, production data to determine the permeability distribution. We then use the permeability distribution and an array of automated simulation predictions to determine infill drilling potential throughout the reservoir.

The likely immediate objection to this proposed approach is that, since it is based on reservoir simulation, it will require a complete reservoir data set, unlike the Mosaic technique. The complete reservoir data set will either not be available or will require a reservoir characterization study, which will increase the times and costs significantly and which will provide no advantage over conventional reservoir studies because it will be, in fact, just like any other reservoir study. This is not the case here.

Our objective is still rapid assessment of infill-drilling potential using only readily-available well locations and production data, thus providing approximate, statistical assessments for significantly less times and costs than conventional reservoir studies. To accomplish this we adopt several strategies. First, we do not conduct a reservoir characterization study. For data other than well locations and production data, we use only what are currently available. For example, if a net thickness map is available, we input it into the simulator; otherwise, we use an estimated average value of net thickness. Second, we use relatively coarse simulation grids, by conventional simulation standards. In conventional reservoir studies, we typically use fine grids because our scope is usually limited to a single reservoir. For infill-drilling studies in unconventional reservoirs, our scope is usually much larger, approaching basin scale in some cases. Thus, we use relatively coarse grids and fewer layers (often only one) to minimize run times and costs and to reduce the number of parameters in the regression. Third, we use different regression parameters than we use in conventional reservoir simulation studies. Instead of matching on individual cell values of reservoir properties (usually permeability), we match on constant values of permeability within the Voronoi regions around each well. Thus, the number of regression parameters is reduced to the number of wells. Fourth, we use different well controls and matching variables. In conventional reservoir simulation history matching, we usually fix the production of the primary hydrocarbon phase and match on reservoir pressure and production ratios, such as GOR and WOR. In the application of our proposed approach to unconventional gas reservoirs, we often have no reservoir pressure data. Thus, we control the wells using an estimated constant flowing bottomhole pressure (a reasonable assumption for low-rate gas wells) and match on production rates.

Using a reservoir simulator in an approximate way like this requires a change in mindset, which may be difficult for some engineers. Because of the assumptions and approximations we make, the results are approximate. However, our tests in single-phase, low-permeability gas reservoirs indicate that the new approach is more accurate than the Mosaic moving window method, with about the same amount of data, time and effort required. Thus, with this approach, in essence, we are using the reservoir simulator as an approximate, scoping tool.

There are a number of advantages to this simulation-based approach. First, it does not require the assumption of uniformity of reservoir properties in windows of 5 to 20 wells, as does the Mosaic method. Second, since it utilizes a reservoir description instead of simplified regression equations, seismic data and other types of geological information can be more readily incorporated than in moving window methods. This should improve the quality of the results and decrease the level of uncertainty. Third, the approach provides a means for gradual transition from preliminary scoping studies to more rigorous, conventional reservoir studies. As more data and interpretations are acquired, the model reservoir description can be updated and the regression repeated. Mosaic and other moving window methods do not provide an easy means for transitioning to more rigorous analyses. Finally, the method can be more-readily applied to stripper oil fields, such as the Cut Bank field, than moving window statistical methods, since reservoir simulators are already capable of modeling multiphase flow.

A key component of this alternative method is robust automatic history matching technology. While we have developed proprietary software for our work in unconventional gas reservoirs, we have elected to use SimOpt in our application to the Cut Bank field. SimOpt is an automatic history matching tool developed by Schlumberger and designed to work with the Eclipse family of reservoir simulation software. It uses mathematical techniques to vary specified reservoir parameters (permeability, in our case) to minimize the difference between observed and simulated production data. It can also take into account prior geological information, when available, in the regression.

Tests on Synthetic Cases

Because of the problems we had with the Cut Bank production data, we decided to first test the new approach on several synthetic cases derived from the SCCBSU. The purpose was to evaluate the capabilities of the software for the automatic history matching process as well as to test the ability to solve a problem where the solution is known beforehand. The synthetic model resembles the actual field in several respects. We used the structure map of the Lower Cut Bank sand, the net pay map from QRI/BEG, and a porosity map from log data. Core data were used to establish a porosity-permeability transform and to map permeability. This permeability map became the "known" permeability distribution for the purposes of testing the regression in the synthetic cases.

For each case, we generated 20 years of oil, gas and water production rates, water injection rates, and bottom hole flowing pressures with the synthetic model, and then performed a regression using SimOpt. We started with a constant permeability value for the entire field, which provides a rigorous test of the regression code. We then attempted to determine the "actual" permeability distribution by matching the synthetic production and injection data. Instead of matching on permeability in each simulation grid block, we matched on the uniform permeability value in the Voronoi region (region of grid cells closer to a well than any other well) surrounding each well, resulting in one matching parameter per well. Even though the resolution of the calculated permeability field would not be the same as the actual permeability field, the object of the regression was to obtain a permeability distribution that would resemble the one used to generate the observed data.

We started with small synthetic cases, all single layer, and increased the size with the successful completion of each case. The smaller cases, e.g., a 54-well case and a 112-well case, could be run on a PC. The computational and memory requirements of

SimOpt are significant, however, and we were required to run larger cases on a Unix workstation. The largest case we ran covered the entire central seismic area and included 192 wells. **Fig. 37** shows the simulation grid and the Voronoi permeability regions around each of the 192 wells in this model. The regression converged within 9 iterations, with a root-mean-square error decreasing from around 400 and to a value close to 100 **(Fig. 38).** **Fig. 39** compares the permeability map used to generate the observed data and the permeability map obtained after the regression. **Figs. 40** and **41** show the best and worst well matches obtained between the simulated results and the observed data. We consider the regression results to be good, especially given that we started with a uniform permeability distribution. Unfortunately, it took 8 hours of machine time per iteration and, thus, 72 total hours to achieve an acceptable match for this problem.

To determine infill-drilling potential, we made performance predictions with the reservoir simulation model and the permeability distribution resulting from the regression of production data. We first made a 20-year base case forecast in which we continue current operations, and then recorded the ultimate recovery. To determine the potential incremental recovery to be realized from drilling an infill well at a particular location, we made a 20-year projection in which we drill and produce one new well at the location (grid block) of interest, and then recorded the incremental recovery to be attributed to the drilling of this well. We then repeated this procedure for every grid block, using an automated procedure, to determine the incremental recovery to be realized from an infill well drilled at all possible locations (grid blocks) in the reservoir.

A map of infill incremental recovery is shown in **Fig. 42**. Visualization of infill potential in this way makes it immediately apparent that there is greater potential for infill drilling in the northwest portion of the field than in the southeast portion. Comparing the infill incremental recovery map to the net pay map (**Fig. 43**) and permeability map (Fig. 39b) indicates that greater infill potential tends to be located in areas of higher permeability and sand thickness corresponding to channel deposits. The procedure also takes into account proximity to existing wells as well as fluid saturations. Thus, the map reflects lower infill potential in areas of high water saturation near existing injection wells.

Since we have used a coarse permeability distribution in the regression (a constant permeability in the region around each well), the calculated permeability is not perfect. To determine the effect of this approximate permeability distribution on the estimation of infill potential, we also constructed an infill incremental recovery map (**Fig. 44**) using the original, “known” permeability distribution (Fig. 39a). The similarity between Figs. 42 and 44 indicates that the imperfect permeability distribution does not affect significantly the conclusions regarding which areas of the field offer the greatest infill potential.

Although the synthetic reservoir models were derived from the SCCBSU, the simulated production and injection performance do not necessarily closely resemble actual Cut Bank performance. In particular, the synthetic models do not experience the rapid water breakthrough, large ratio of water injection to fluid production, and low incremental waterflood recoveries that are observed in the SCCBSU. We attribute these waterflood performance characteristics to gravity segregation combined with generally higher permeability at the base of the Cut Bank sand (consistent with the generally upward-fining log signatures), neither of which are captured in the single-layer synthetic models. Nonetheless, these cases demonstrate the viability of the simulation-based approach, which was the objective of the synthetic modeling.

Analysis of Actual Cut Bank Production Data

With good results from the synthetic modeling, we next attempted to analyze the actual production and injection history from the central seismic area of the SCCBSU. The actual data set includes production and injection data for 172 wells for approximately 71 years of history, the last 40 years being the waterflood. Instead of starting with a uniform permeability distribution, we started the regression with an initial permeability distribution (**Fig. 45**) derived from a correlation between core porosity and permeability data.

We started with a 5-layer model, thinking it necessary to model gravity segregation and the vertical distribution of permeability in the Cut Bank sand if we were to match actual SCCBSU performance data well. This proved impossible, however, due primarily to software problems and limitations. The SimOpt software that we are using for automatic history matching is general-purpose software designed to manage efficiently up to 50 parameters in the regression. We are using more than 3 times this number of parameters and are, thus, stretching its capabilities significantly. In addition, with 71 years of history, iterations take considerably longer than the 8 hours per iteration required for the 20-year synthetic case, making the multi-layered analysis impractical.

Ultimately we conducted a single-layer analysis. This required a two-step process. In the first step we used pseudo relative permeability curves to obtain a rough match of the overall SCCBSU producing water-oil ratio. Using pseudo relative permeability curves reproduces the water bypassing effects due to gravity segregation and higher permeability near the base of the Cut Bank sand. **Figs. 46-48** show comparisons of simulated to observed performance on a field-wide basis.

The second step was to regress the production and injection data to refine the permeability distribution. The regression attempt was unsuccessful. It resulted in very little improvement in the match, and yielded formation permeabilities that were unreasonably high in parts of the reservoir. We attribute the inability to get a reasonable match to both software limitations and problems with the production and injection database. As mentioned previously, we are exceeding the recommended maximum number of regression parameters by more than a factor of 3. While this may limit the robustness of the solution, more importantly, it results in memory and computational requirements that make solutions intractable. We think the greater cause, however, is problems with the production and injection database, in particular, the lack of individual well production data. During the approximately 20-year period in which we have only unit-wide production, production is necessarily allocated among wells. This introduces the potential for significant error in individual-well production rates, which would obviously affect significantly the accuracy of results based on these individual-well data.

Thus, the model resulting from the field-wide match of water-oil ratio in step one (permeability map in Fig. 45 and match results in Figs. 46-48) represents our best model of the SCCBSU at this time. We ran our automated infill incremental recovery determination procedure using this model, which resulted in the map shown in **Fig. 49**. Examination of Fig. 49 indicates that greater infill potential occurs in the western portion of the region than in the east. This is reflective of higher water saturations in the eastern portion, due to the start of waterflood operations in the eastern portion 20 years prior to the start of waterflooding in the western portion. The large area colored in red, corresponding to a relatively uniform upper limit on infill recovery, in a consequence of the well constraints employed in the simulated projection runs. We specified a target oil rate of 200 STB/D for the new infill production well in the projections. The areas in red correspond to locations in which the new infill well was able to maintain the target rate over essentially the entire 5-year projection period. Areas of lower infill recovery in the midst of the red areas correspond to either lower pore volume or permeability, or proximity to injection wells.

Given the incomplete regression and problems with the production/injection database, we caution that there is considerable uncertainty in these results. Further study is required to select specific infill locations.

Discussion

We believe the simulation-based analysis of the actual SCCBSU data was not completely successful in large part due to problems and omissions in the production and injection database. We note that the other two methods that we employed, the Mosaic and the Albertoni-Lake methods, are also adversely affected. Any method that is based primarily on analysis of production and injection data, as these three methods are, will be adversely affected by inaccuracies in the production and injection database. We were not aware of the problems with the Cut Bank production data at the beginning of the project. In hindsight, it is clear that this was not the best field case for demonstrating application of these methods. We continue to believe that statistical methods for rapid assessment of infill and recompletion potential, particularly the simulation-based method that we have presented, can be valuable reservoir management tools for operators of marginal stripper fields. However, while they may cost significantly less than complete, integrated reservoir studies, they are not without costs. Time, effort and money must be spent in construction and quality control of the production database for the methods to be of use. The results can be no better than the quality of the data.

That we were able to match a synthetic model of the SCCBSU with 192 wells indicates the viability of our simulation-based methodology for rapid assessment of infill potential. Given its superiority over moving-window statistical methods, we recommend that future research in this area be focused on continued development and validation of the simulation-based regression approach. However, it may not be practical with the regression software technology that we are currently employing. Fit-for-purpose software may be required for this application, particularly for larger stripper fields with many more wells, which is our intended use of the methodology. Researchers in the Petroleum Engineering Department at Texas A&M University are currently working on a new generation of simulation regression tools that appear to be much more powerful and efficient than existing commercially available software.

Finally, based on our work in this and other research projects, we believe that greater benefit of the Mosaic and simulation-based regression techniques will be realized in unconventional and stripper gas reservoirs than stripper oil reservoirs, at least in the near term. Gas reservoirs are less often affected by multiphase flow, and they are less sensitive to other parameters such as PVT properties. Consequently, there are fewer degrees of freedom in the regression of gas reservoirs than oil reservoirs, particularly waterflooded oil reservoirs. We recommend that continued research on rapid infill assessment tools be directed towards gas reservoirs in the near term. Once the technology is well proven in stripper gas reservoirs, the focus can be shifted to the more complex stripper oil fields.

CONCLUSIONS

1. Maximum seismic amplitude varies inversely with well log porosity (R^2=0.51) in the Lower Cut Bank Sand. This correlation between seismic amplitude and log porosity enables the use of seismic data to map porosity trends for use in production data analysis.
2. Problems and omissions in the SCCBSU production database limit the effectiveness of all the rapid infill assessment techniques we investigated, since these techniques rely primarily on analysis of production and injection data. The SCCBSU production database is incomplete due to data loss as the unit changed operators during its history.
3. The Mosaic moving window statistical method is not suitable for analysis of SCCBSU production and injection data. The channelized nature of Cut Bank sand deposits results in significant variations in reservoir properties well to well, which are inconsistent with the Mosaic assumption of relative uniformity of reservoir properties in windows (local neighborhoods) of 5-20 wells.
4. Interwell connectivity evaluations, using the Albertoni and Lake (2003) method, give useful indications of well interconnection for the Cut Bank field. The connectivity appears to be strongly anisotropic and influenced by the fluvial geometry of the reservoir. The QRI/BEG net sand pay map gave better agreement with the connectivity maps than did the older, Unocal map.
5. The Albertoni and Lake method may provide a qualitative indication of possible infill well locations. However, it does not provide a means of assessing potential infill well incremental recovery.
6. The simulation-based regression approach appears to be superior to the Mosaic technique in rapidly assessing infill potential due to its (a) similar time and cost requirements, (b) greater accuracy, (c) ability to more readily incorporate other data types, and (d) multiphase capability.
7. In synthetic cases derived from the SCCBSU, the simulation-based regression approach successfully identified infill well locations with significant incremental

potential. Infill potential was concentrated in incompletely swept channel deposits.

8. Analysis of actual SCCBSU production and injection data using the simulation-based regression approach was unsuccessful, due to both problems with the SCCBSU production and injection database and limitations in existing commercially-available regression technology.
9. The simulation-based regression approach should be refined and proven on gas reservoirs before the technology is transferred to more complex oil reservoirs.

REFERENCES

Albertoni, A, and L. W. Lake, 2003, Inferring Interwell Connectivity From Well-Rate Fluctuations in Waterfloods, SPEREE, v. 6, p. 6-16.

Berkhouse G.A., 1985, Sedimentology and diagenesis of the Lower Cretaceous Kootenai Formation in the Sun River Canyon Area, Northwestern Montana, M.S. Thesis, Indiana University, 152 pages.

Cupps, C.Q., and J. Fry, 1966, Reservoir oil characteristics, Cut Bank field, Montana: U.S. department of Interior, Bureau of Mines, 36 pages, illus., tables.

DeAngelo M.V, and B.A Hardage, 2001, Using 3-D seismic coherency and stratal surfaces to optimize redevelopment of waterflooded reservoirs, Cut Bank Field, Montana, The University of Texas at Austin. Bureau of Economic Geology, Geological Circular GC0101, 23 pages.

Guan, L., McVay, D.A., Jensen, J.L., and Voneiff, G.W., 2002, Evaluation of a Statistical Infill Candidate Selection Technique, paper SPE 75718 presented at the SPE Gas Technology Symposium, Calgary, Alberta, April 30-May 2.

Gully T.G., 1984, Cut Bank field, *in* Tonnsen J. ed., Montana Oil and Gas Fields Symposium: Montana Geological Society, Volume 1, p. 397-409.

Hill R., 1989, Geologic evaluation of S.C.C.B.S.U. and recommendations for future development: Union Oil Company of California, In-house Report

Hopkins J.C., 1993, Mesozoic depositional environments, Great Falls, Montana: Caesar Geological Consultants Ltd., Field Trip Report.

Horkowitz K.O., 1987, Direct and indirect control of depositional fabric on porosity, permeability, and pore size and geometry. Differential effect on sandstone subfacies on fluid flow, Cut Bank sandstone, Montana: PhD Dissertation, University of South Carolina, 136 pages.

Hudson, J., Jochen, J., and Spivey, J., 2001, Practical Methods to High-Grade Infill Opportunities Applied to the Mesaverde, Morrow, and Cotton Valley Formations, paper SPE 68598 presented at the SPE Annual Technical Conference and Exhibition, Dallas, 2-3 April.

Matthies P. E., 1962, Evaluation of future operations south central area of Cut Bank field, Glacier County, Montana: Union Oil Company of California, In-house Report.

Quicksilver Resources, 2002, Cut Bank field database.

Reese, R.D., 1996, Completion Ranking Using Production Heterogeneity Indexing, paper SPE 36604 presented at the SPE Annual Technical Conference and Exhibition, Denver, Colorado, 6-9 October.

Shelton J. W., 1967, Stratigraphic models and general criteria for recognition of alluvial, barrier-bar, and turbidity-current sand deposits: American Association of Petroleum Geologists Bulletin, v. 51, No. 12, p. 2441-2461.

Stanulonis S.F., and H.V. Tran, 1992, Method to determine porosity-thickness directly from 3-D seismic amplitude within the Lisburne carbonate pool, Prudhoe Bay, The Leading Edge, p. 14-20.

Voneiff, G.W. and Cipolla, C., 1996, A New Approach to Large-Scale Infill Evaluations Applied to the Ozona (Canyon) Gas Field, paper SPE 35203 presented at the SPE Permian Oil and Gas Recovery Conference, Midland, Texas, 27-29 March.

Weimer, R. J., and R.W. Tillman, 1982, Sandstone reservoirs, SPE 10009.

LIST OF ACRONYMS AND ABBREVIATIONS

QRI – Quicksilver Resources Inc.;

BEG – Bureau of Economic Geology;

SCCBSU - South Central Cut Bank Sand Unit ;

NCCBSU - North Central Cut Bank Sand Unit;

NWCBSU- North West Cut Bank Sand Unit;

pu - porosity unit;

PHIA - neutron-density average porosity;

VSP – Vertical Seismic Profile;

AL - Albertoni-Lake technique;

Np - cumulative oil produced;

λ- fraction of flow in a producer attributable to flow at an injector

Measurement Units Conversion

1 barrel = 158.987295 liters;

1 ft = 0.3048 m;

1 acre= 4046.856422 m^2.

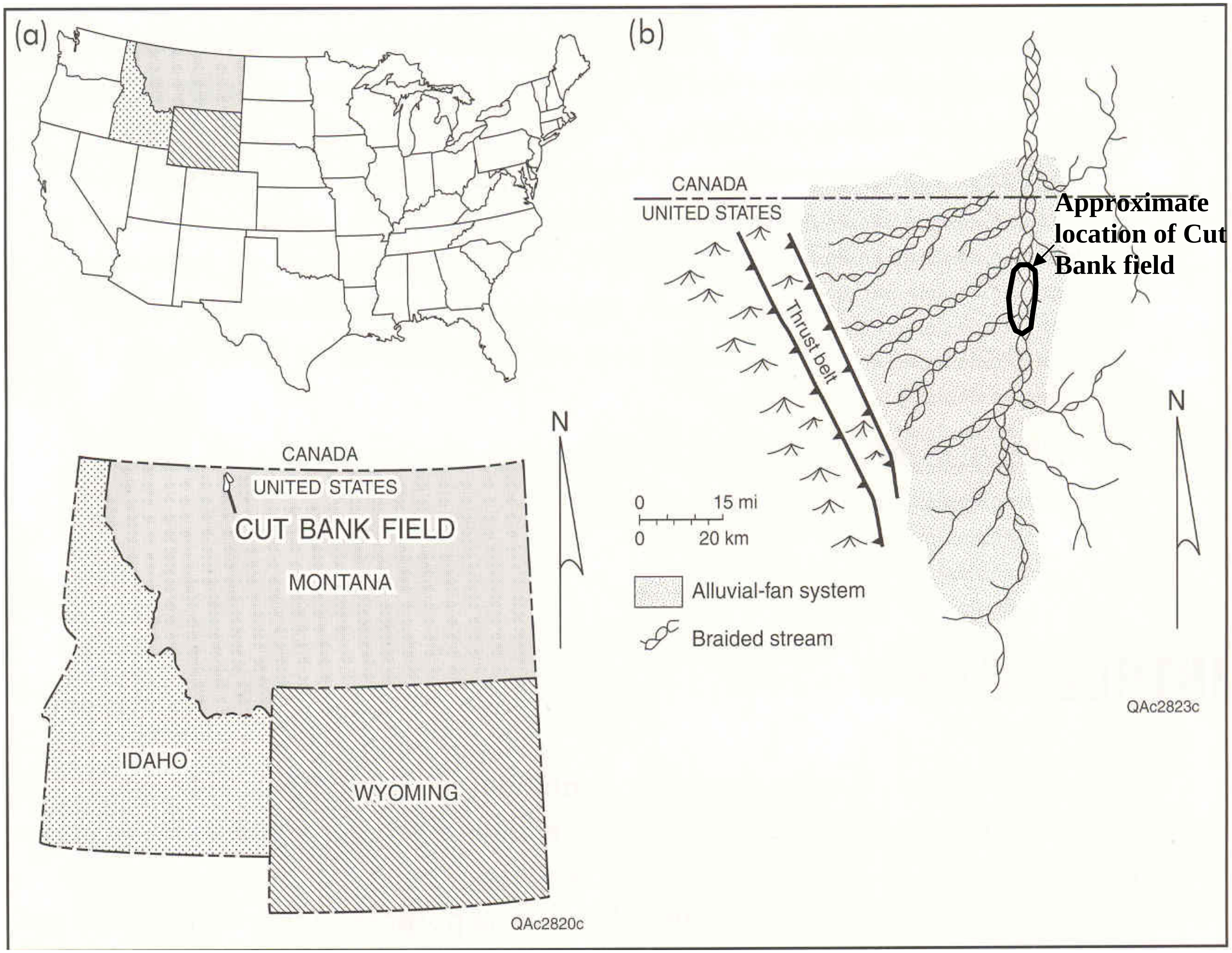


Fig 1. (a) Regional and (b) depositional settings of Cut Bank field (after J.F.Treckman, MSR Exploration, 1996).

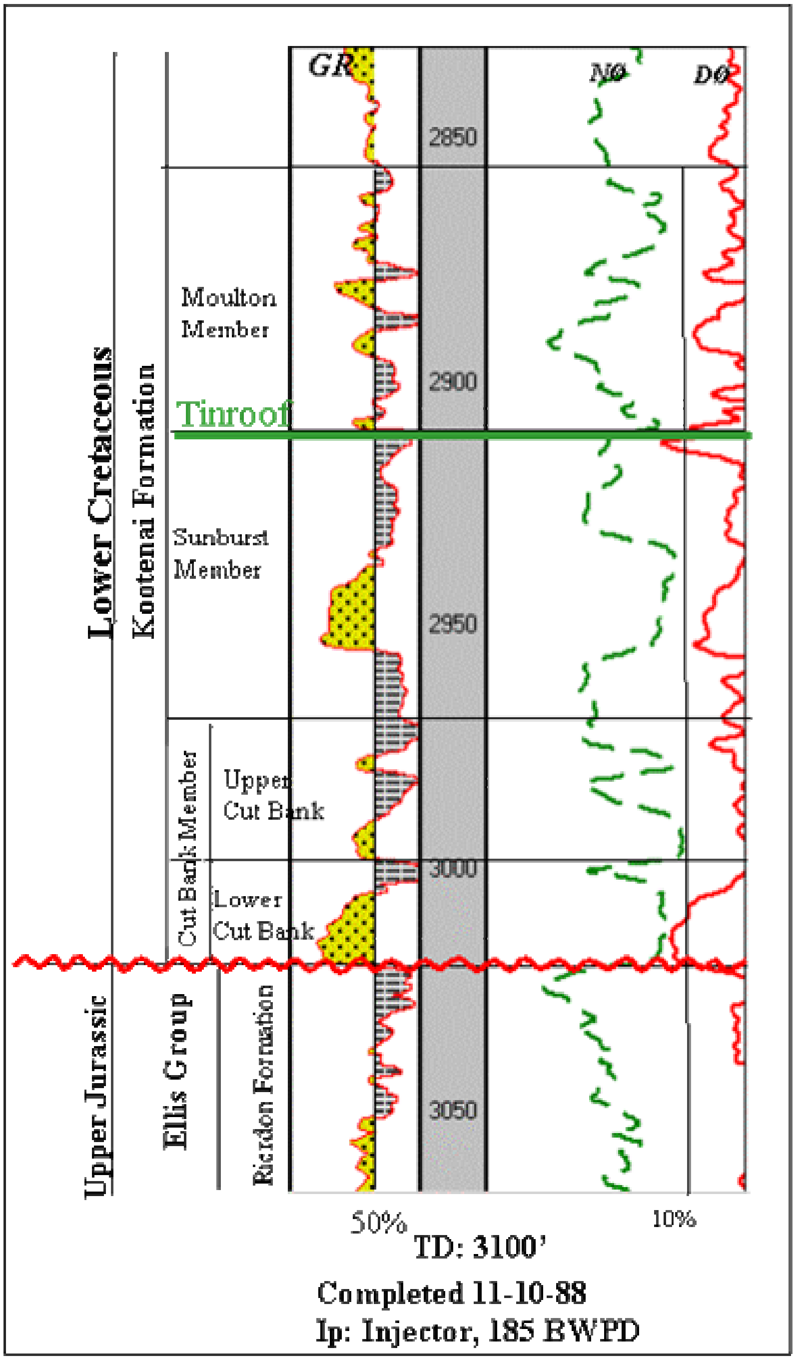


Fig. 2. Cut Bank Field – type log. Well SCCBSU 51-6.

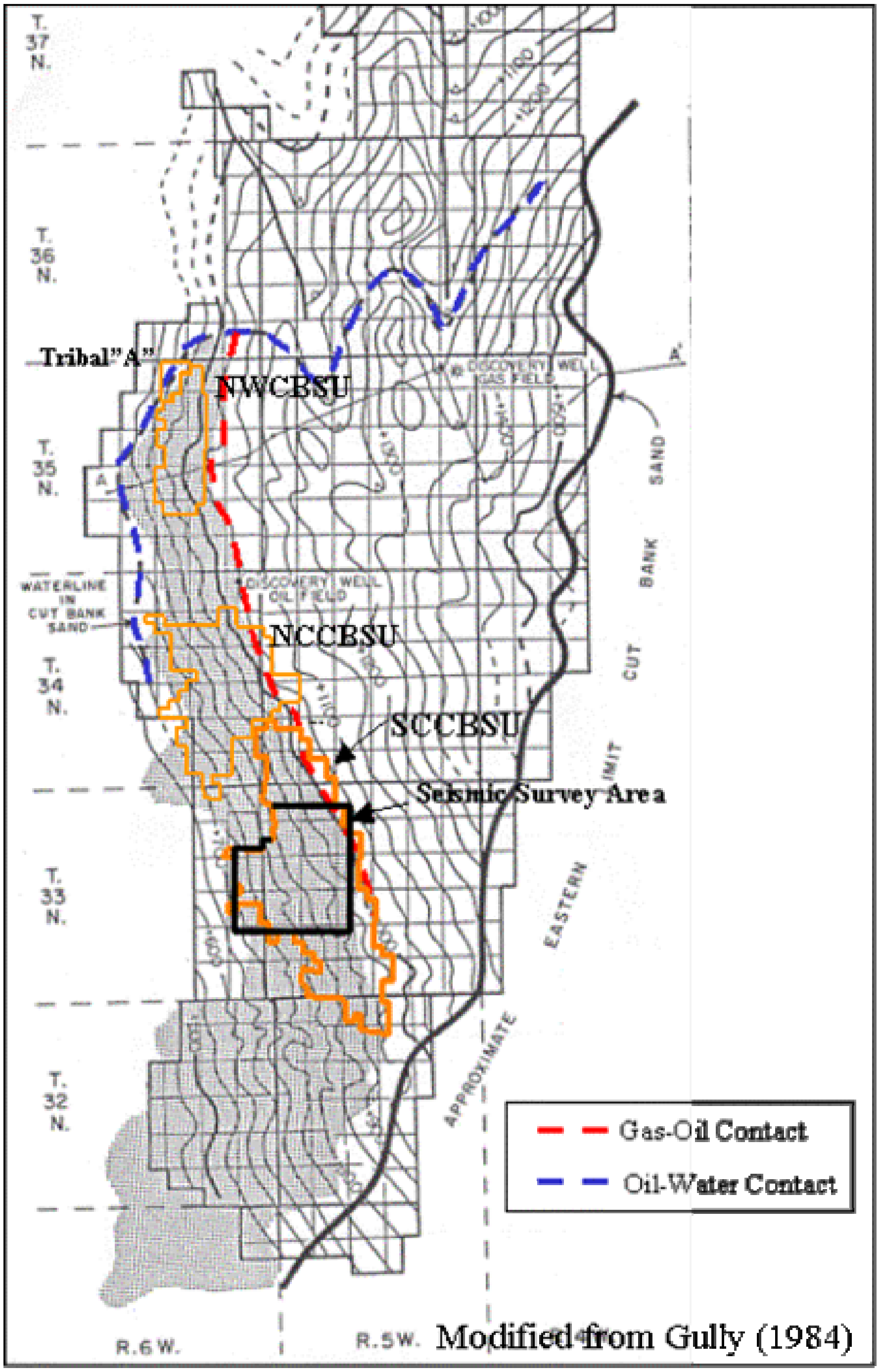


Fig. 3. Cut Bank field, generalized top of Ellis structure. Shaded area correspond to oil leg. Outlines are Cut Bank Units and 3-D seismic survey area (Modified from Gully, 1984).

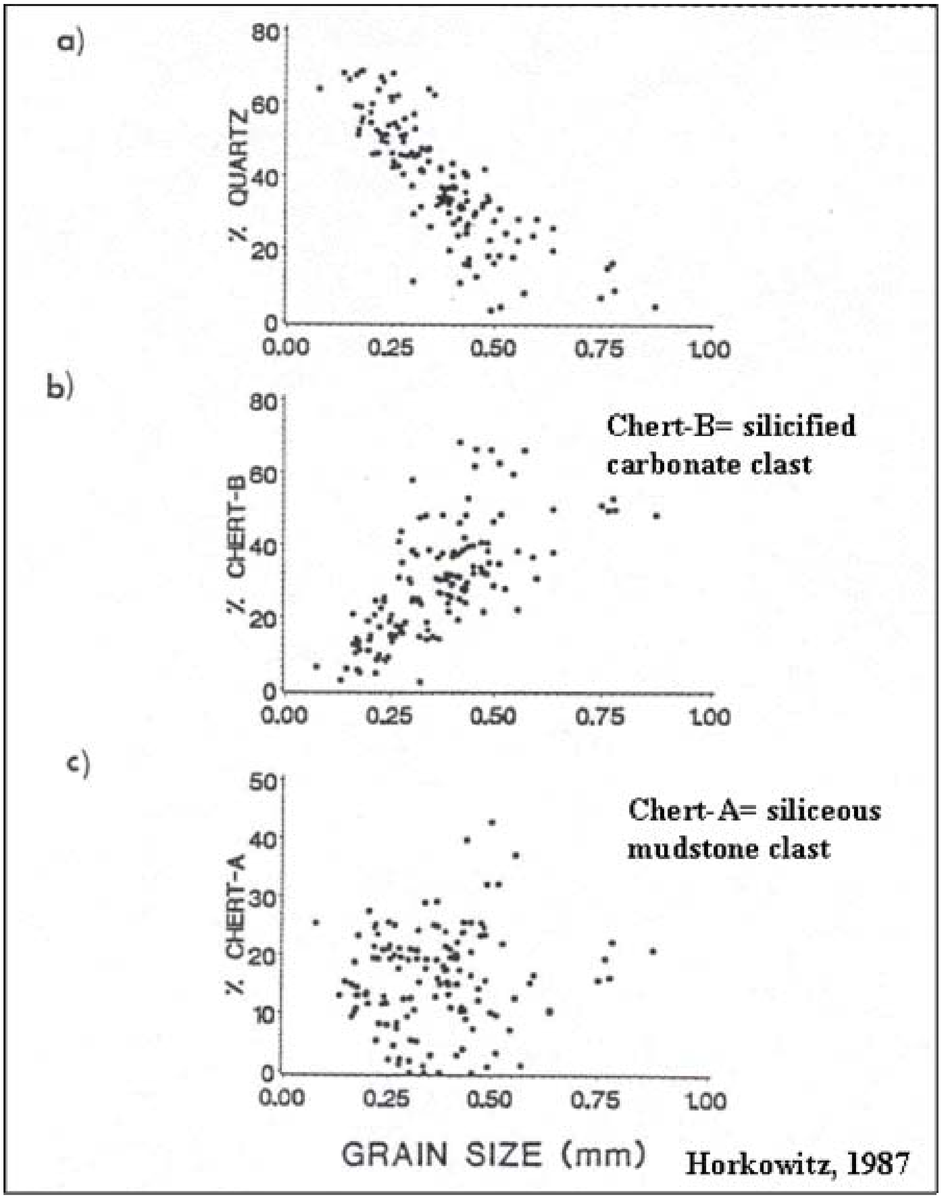


Fig 4. Relation between grain size and framework grain composition, Cut Bank field (Horkowitz, 1986).

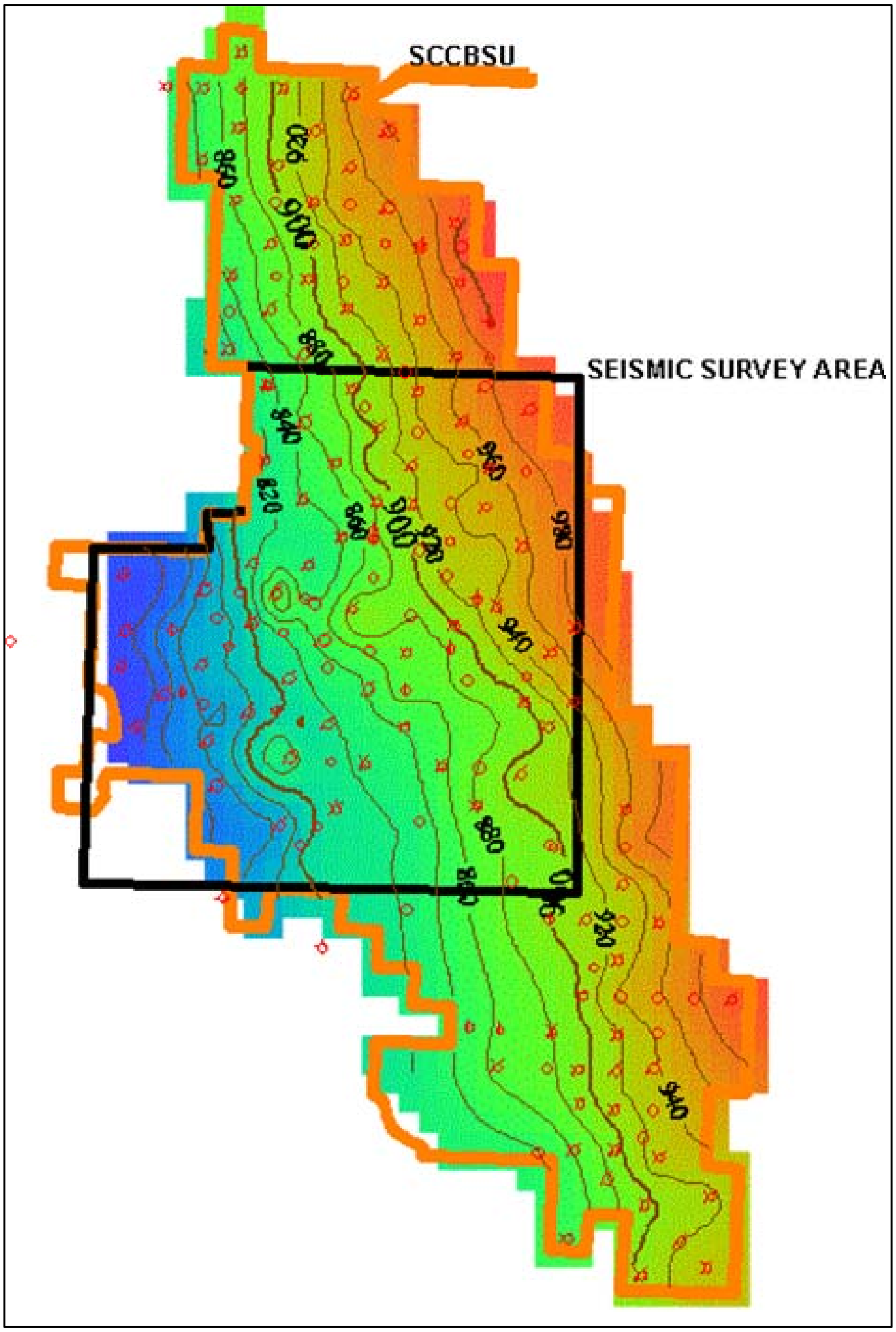


Fig. 5. SCCBSU: Structure map, top of the Ellis Group.

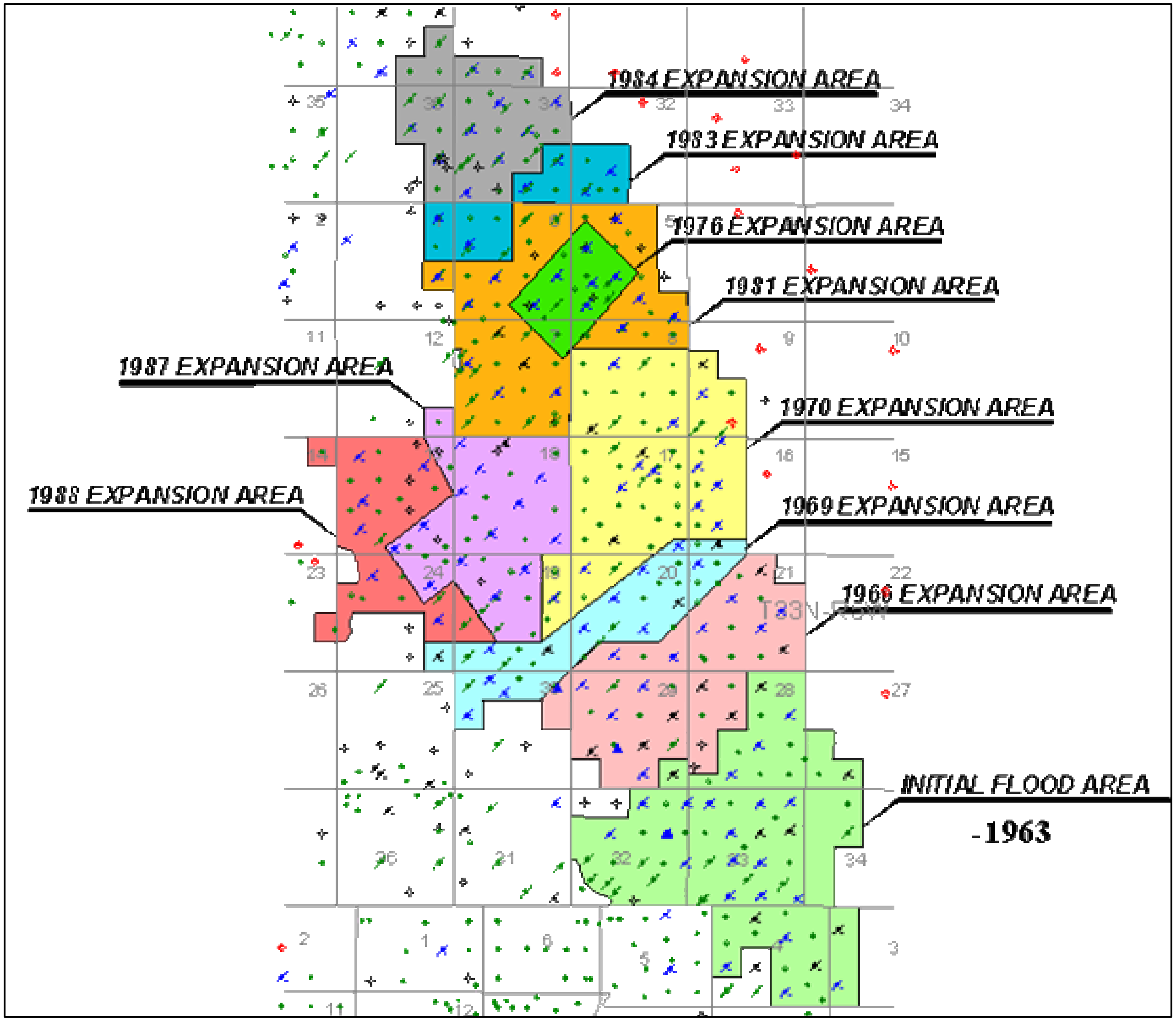


Fig. 6. SCCBSU water flood expansion history (from Quicksilver Resources, 2001).

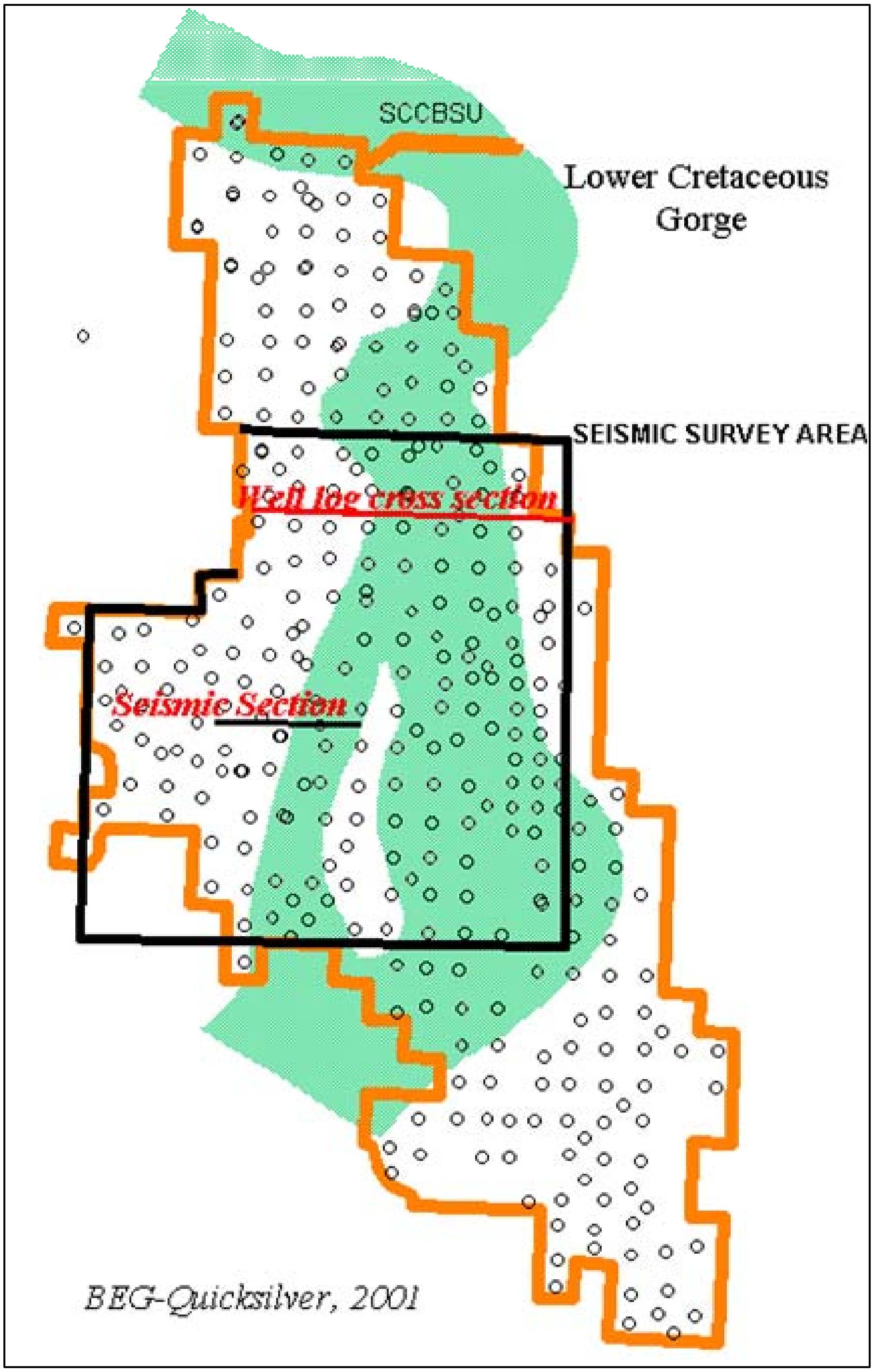


Fig. 7. South Central Cut Bank Unit. Shaded area corresponds to Lower Cretaceous Gorge where the "Tinroof" is absent (from BEG-Quicksilver Resources, 2001).

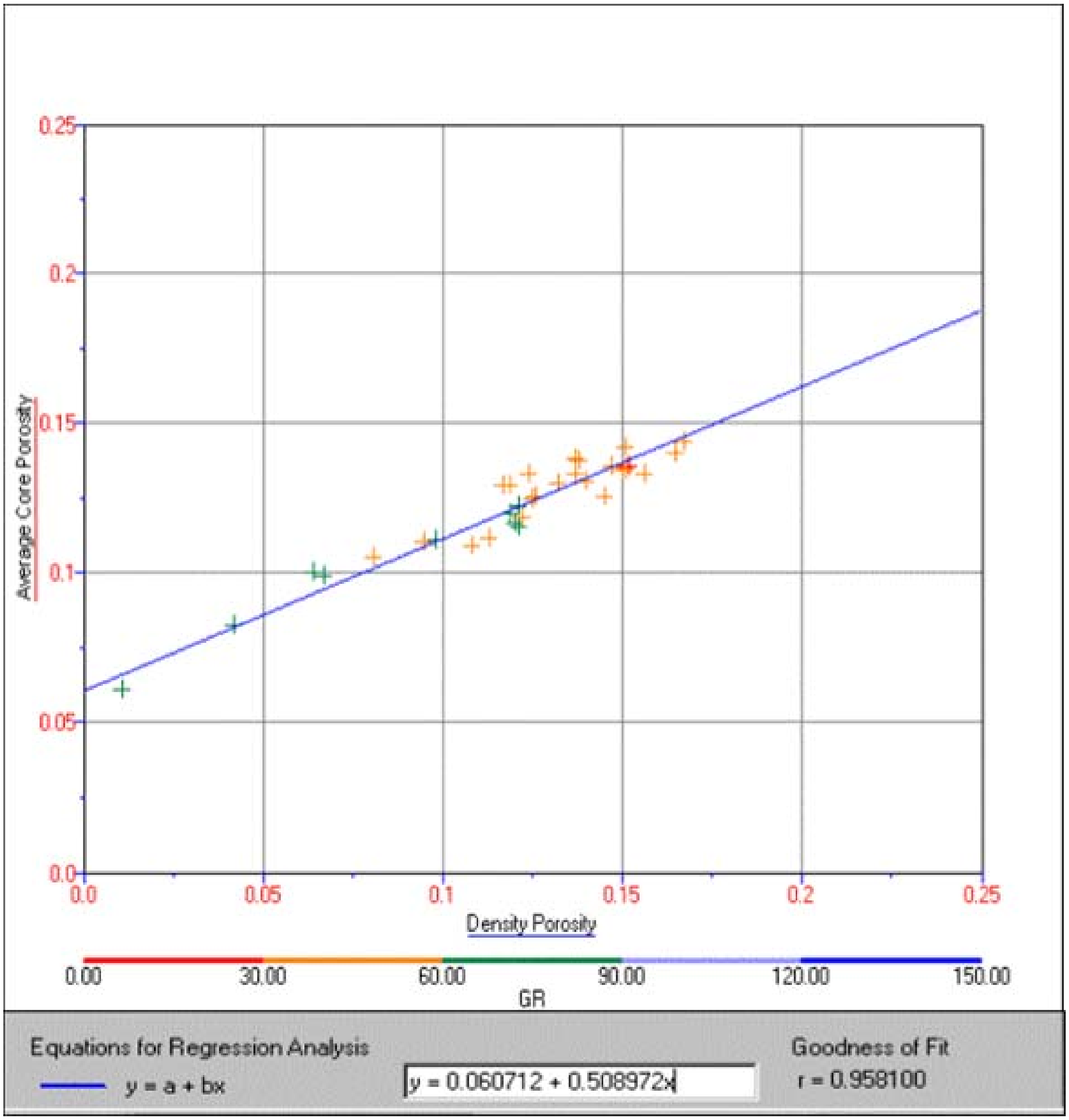


Fig. 8. Well 37-7 - Core-well log porosity calibration for Lower Cut Bank Sand.

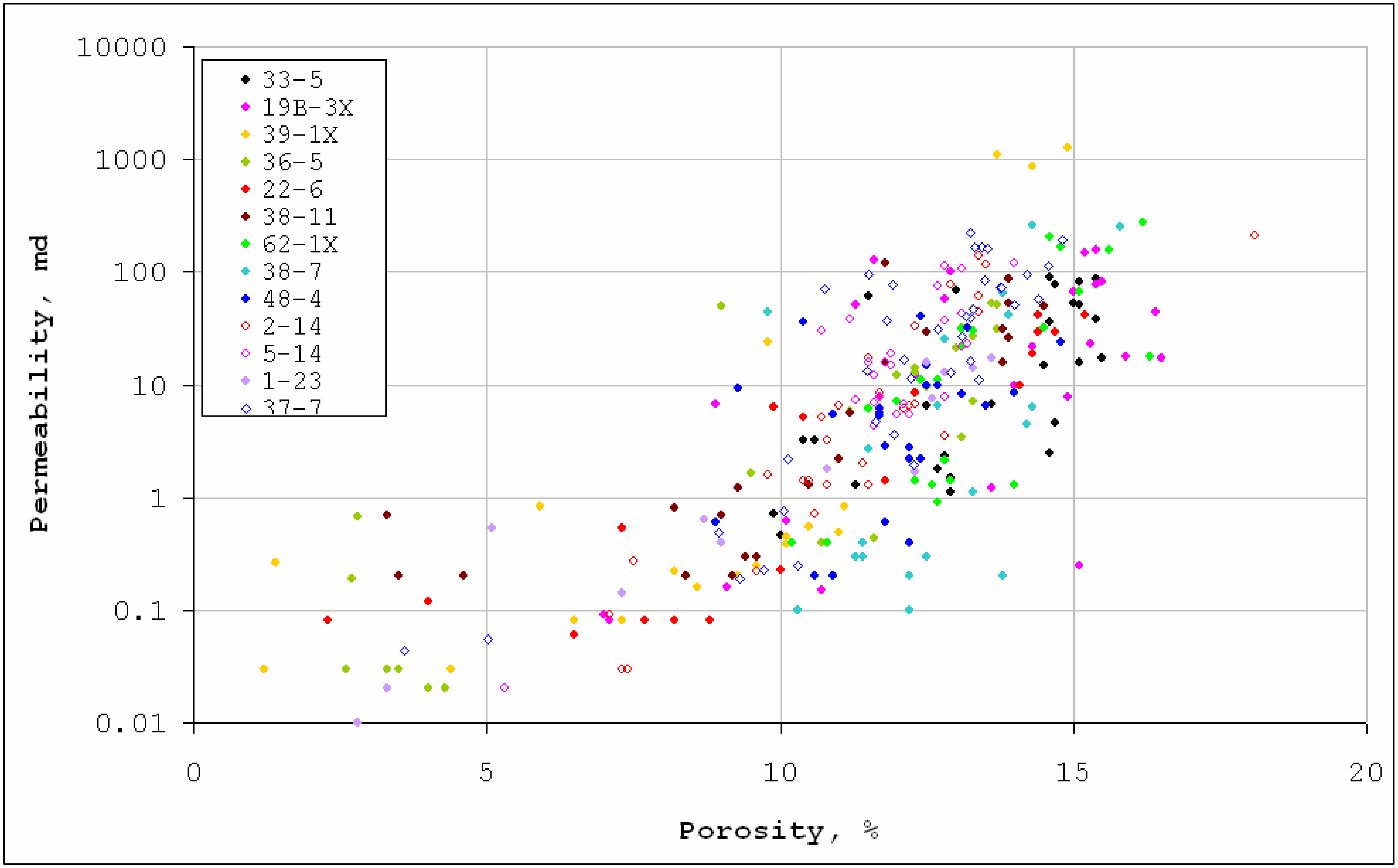


Fig. 9. Core porosity-permeability crossplot .

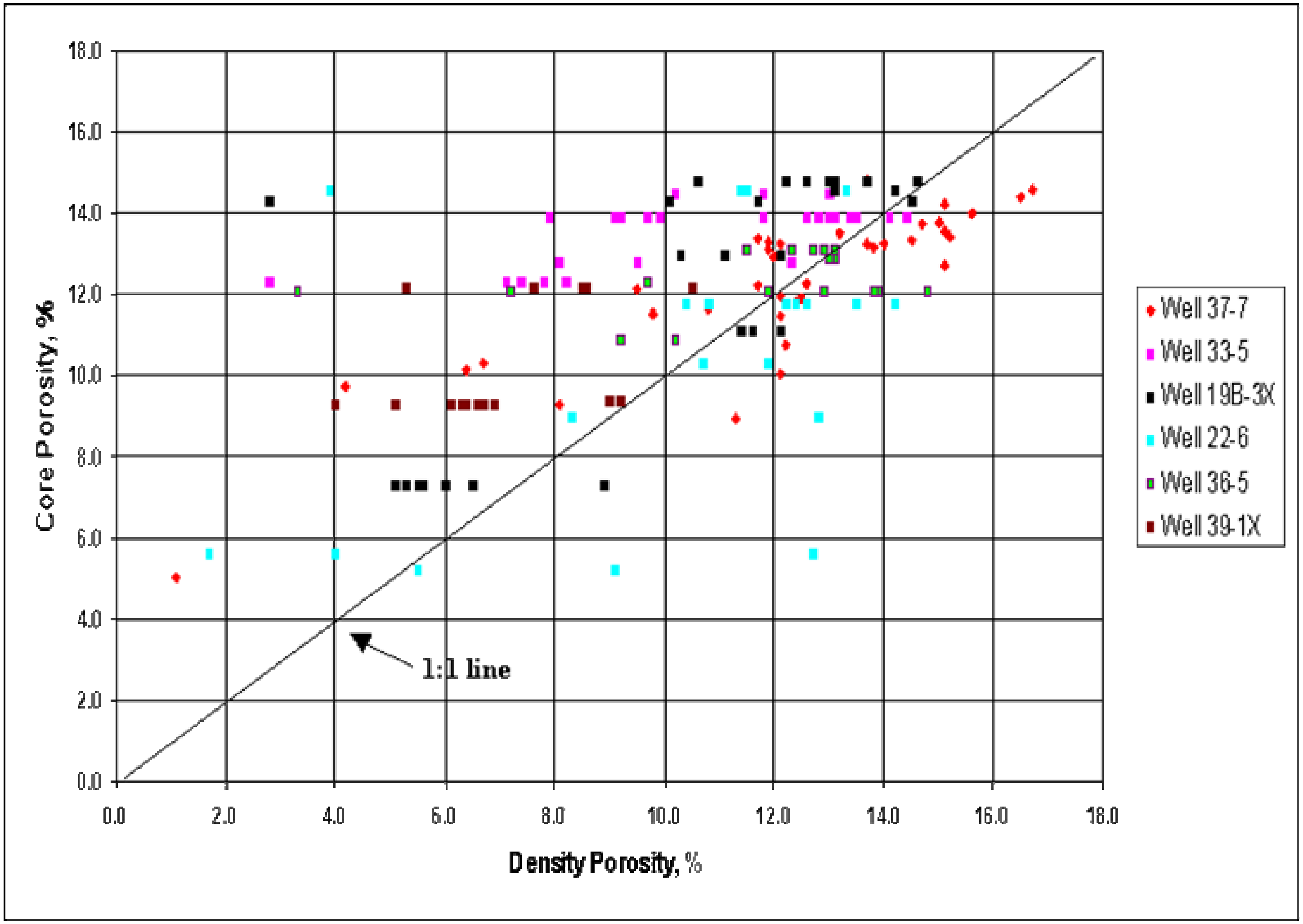


Fig. 10. Core vs. density porosity comparison for all cored wells in the Cut Bank Sand.

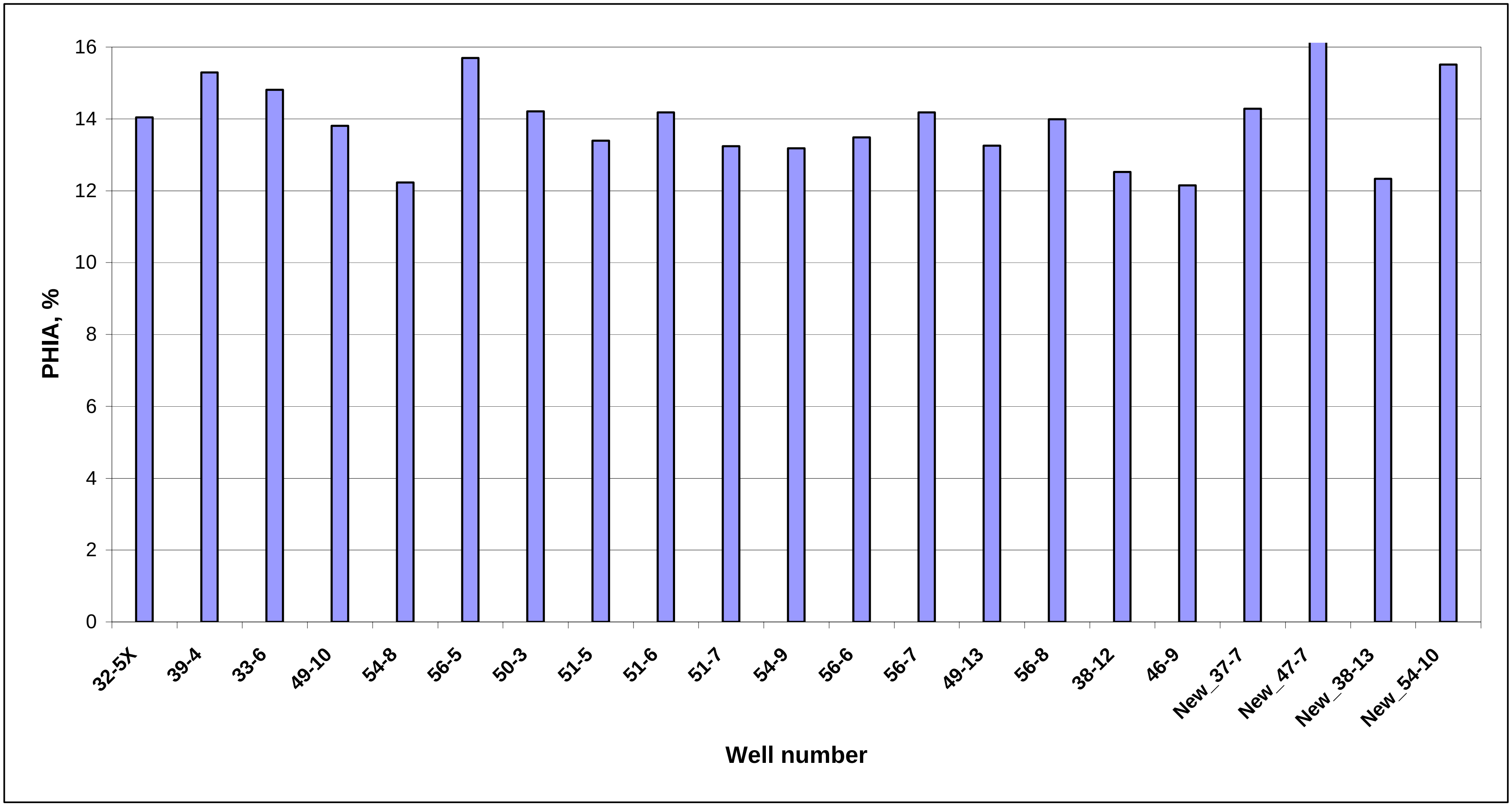


Fig. 11. Neutron-density average porosity values for net pay in the Lower Cut Bank Sand. Net pay is based on a 10% porosity cutoff.

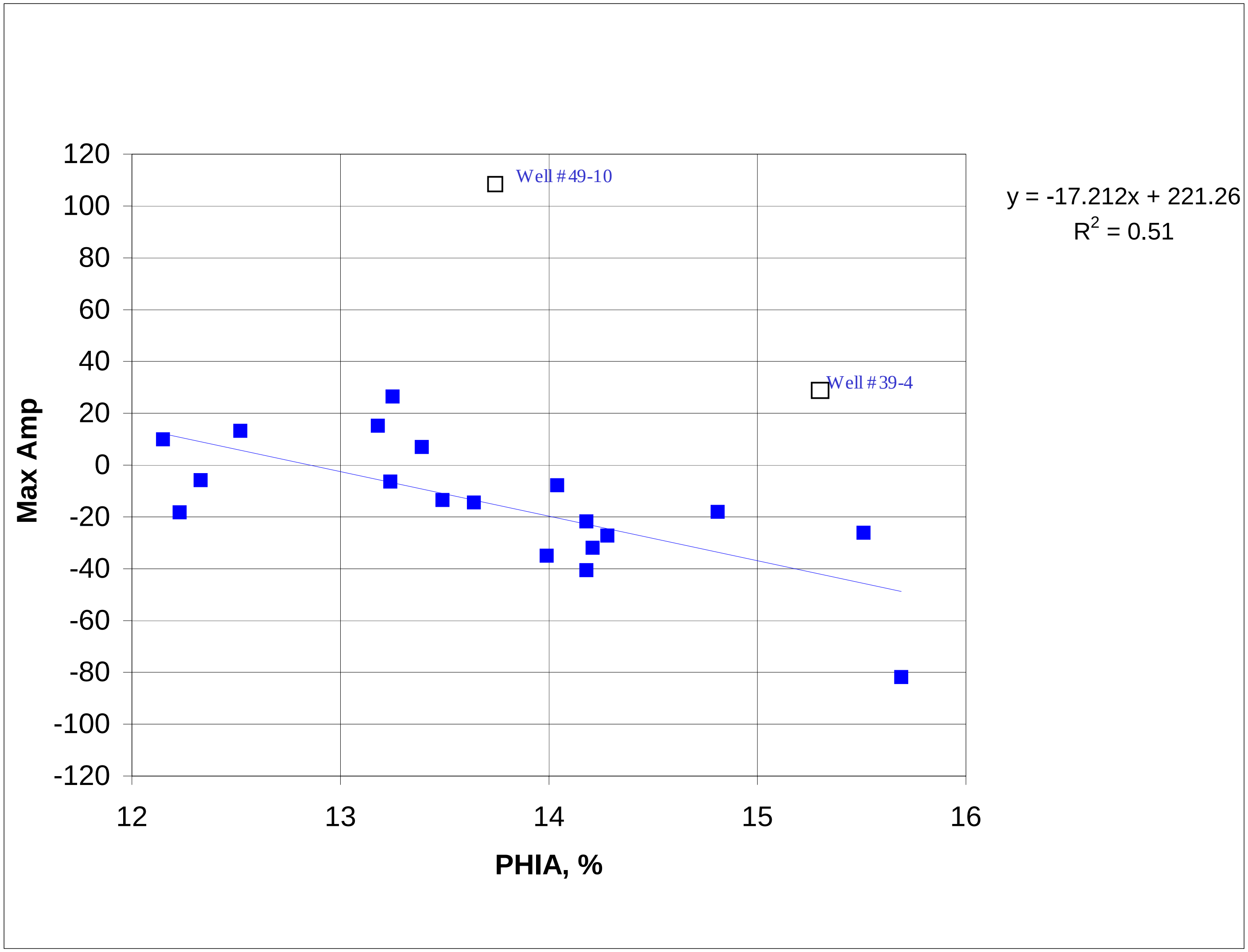


Fig. 12 . Relation between the log neutron-density average porosity and 3-D seismic amplitude at the well ties. Each point represent a well with a given single character name. The empty squares are the excluded wells.

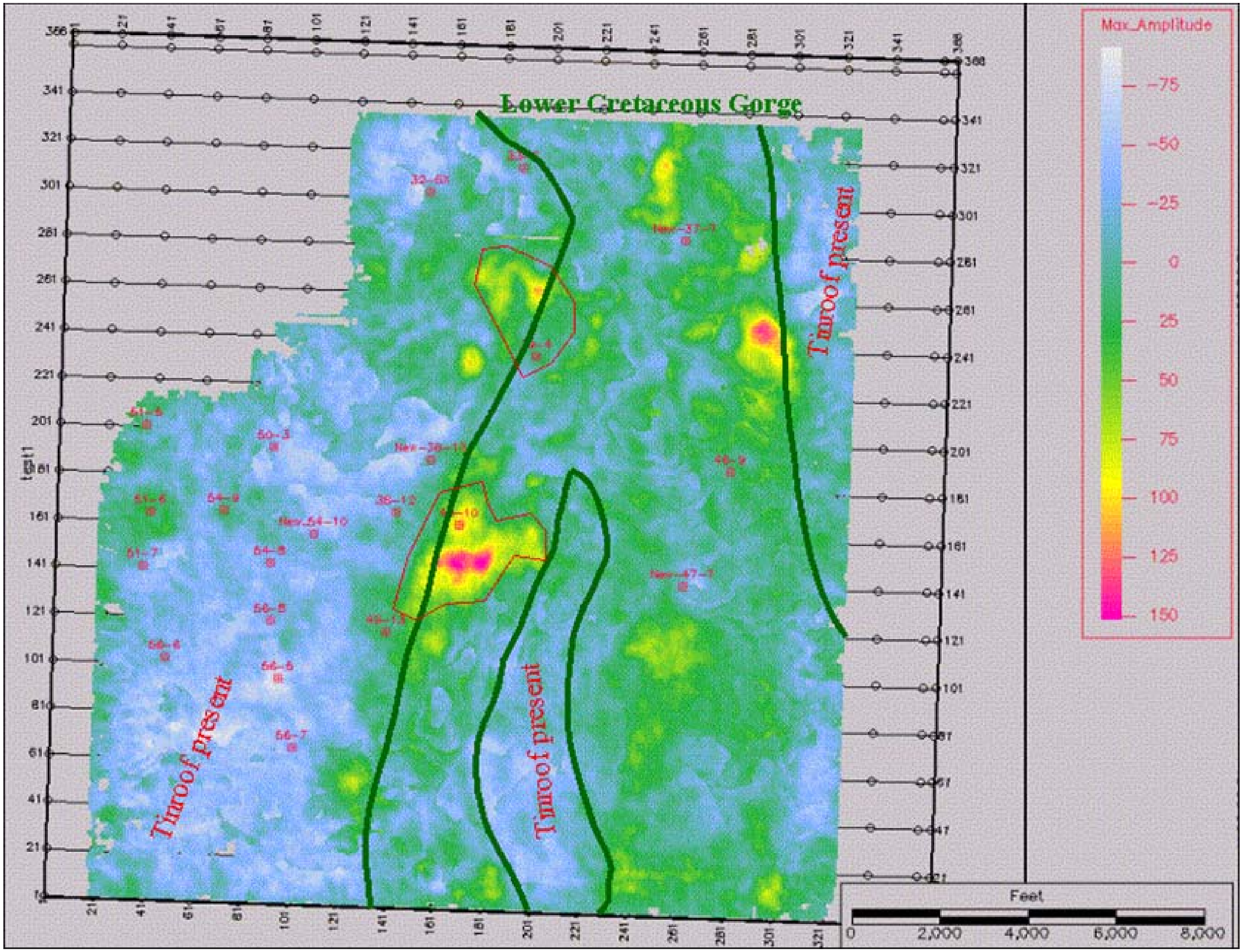


Fig. 13. Maximum amplitude of Lower Cut Bank horizon. Red is highest amplitude and blue is lowest. Red polygons are areas of mismatch.

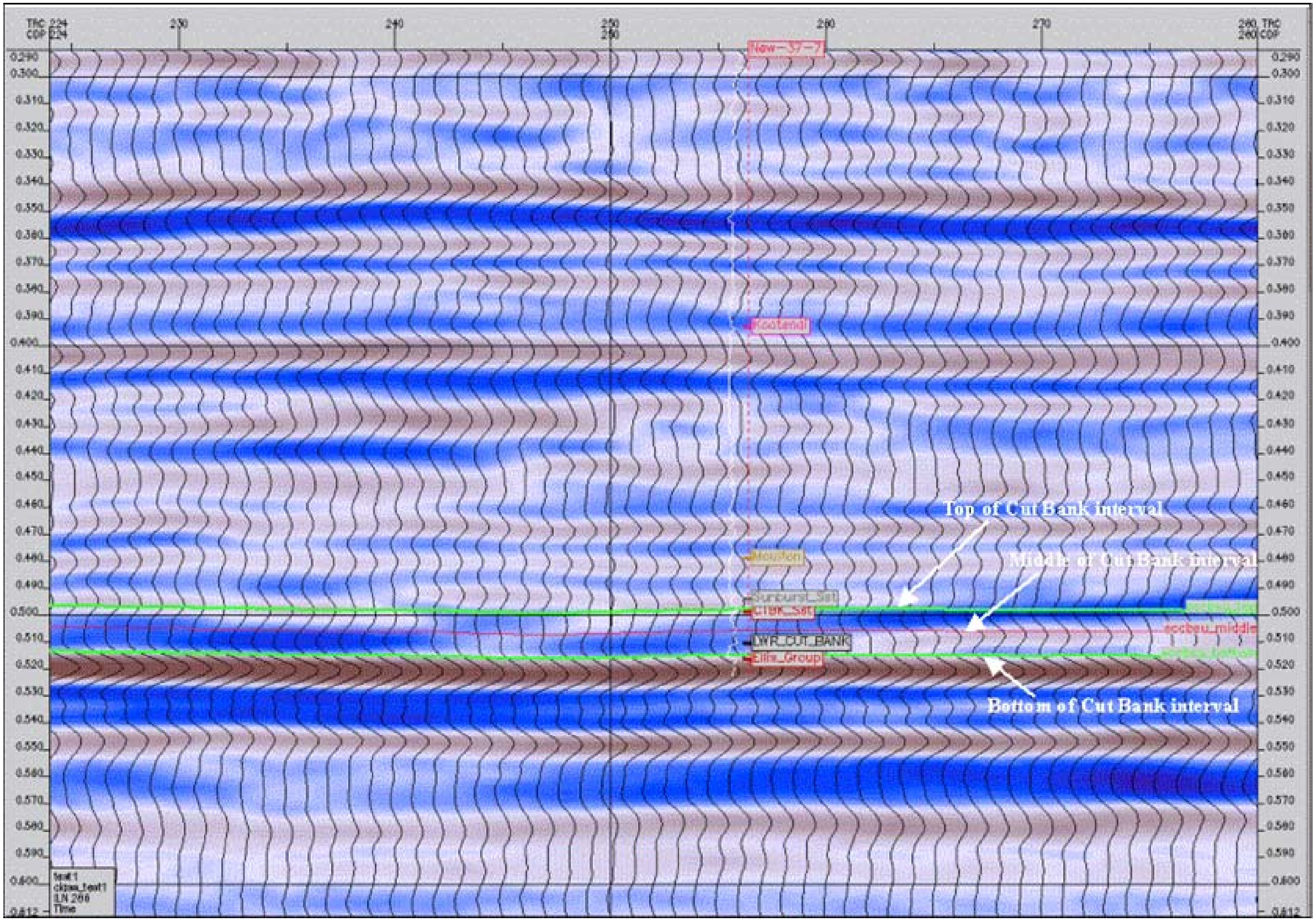


Fig. 14. Seismic section along inline 286 displaying upper, middle , and lower bounding stratal surfaces. Notice the bottom of Lower Cut Bank interval, or top of Ellis, is at the zero crossing above the positive amplitudes.

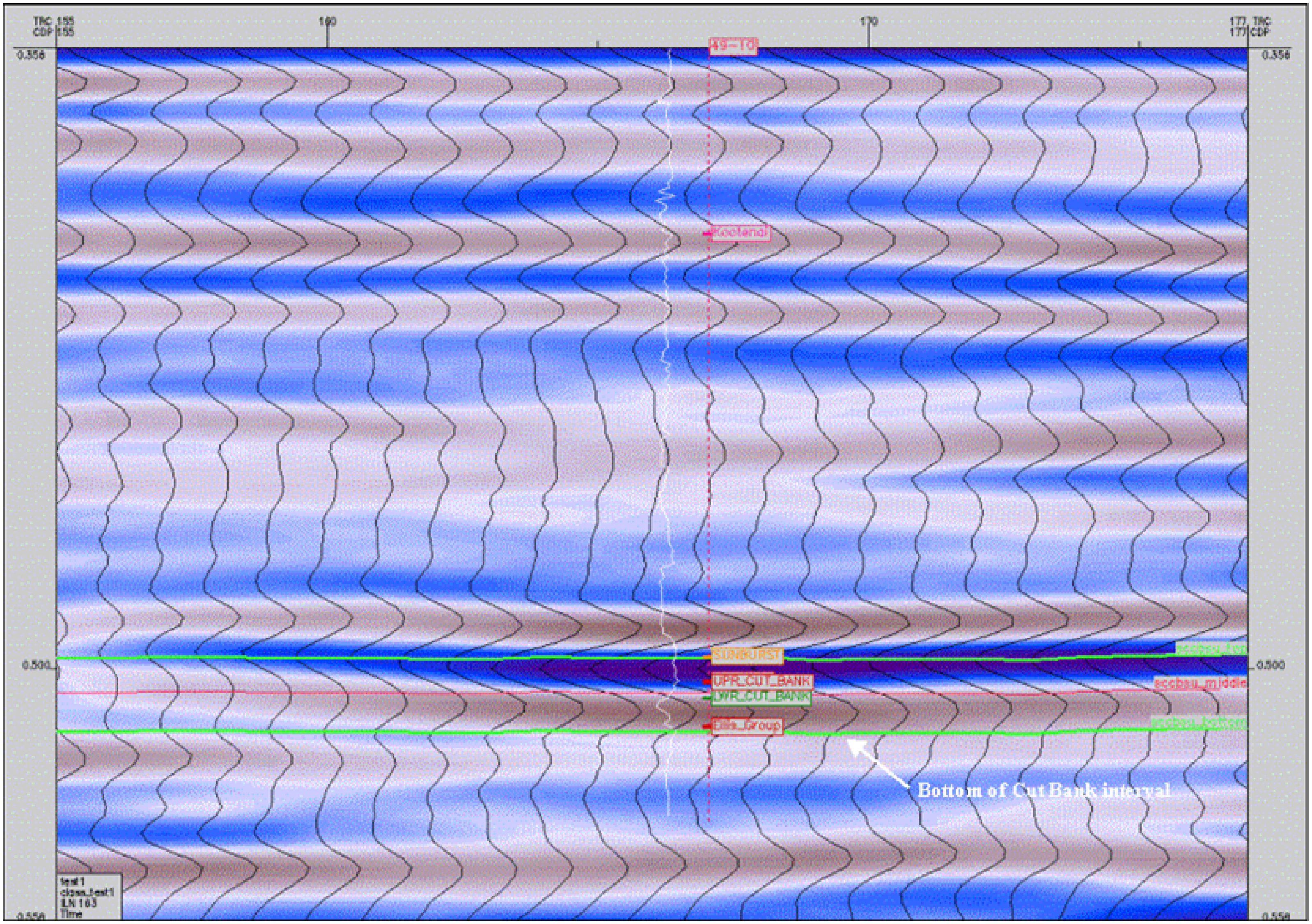


Fig. 15. Seismic section along inline 163 displaying upper, middle , and lower bounding stratal surfaces. Maximum amplitude at Well 49-10 is anomalously high compared to the average log porosity value. One reason for that may be inconsistency of interpretation of the bottom of the Lower Cut Bank strata (Ellis top) in this area. This surface is at the zero crossing above the positive amplitudes all over the seismic survey (see Figure 14) except the area of problem.

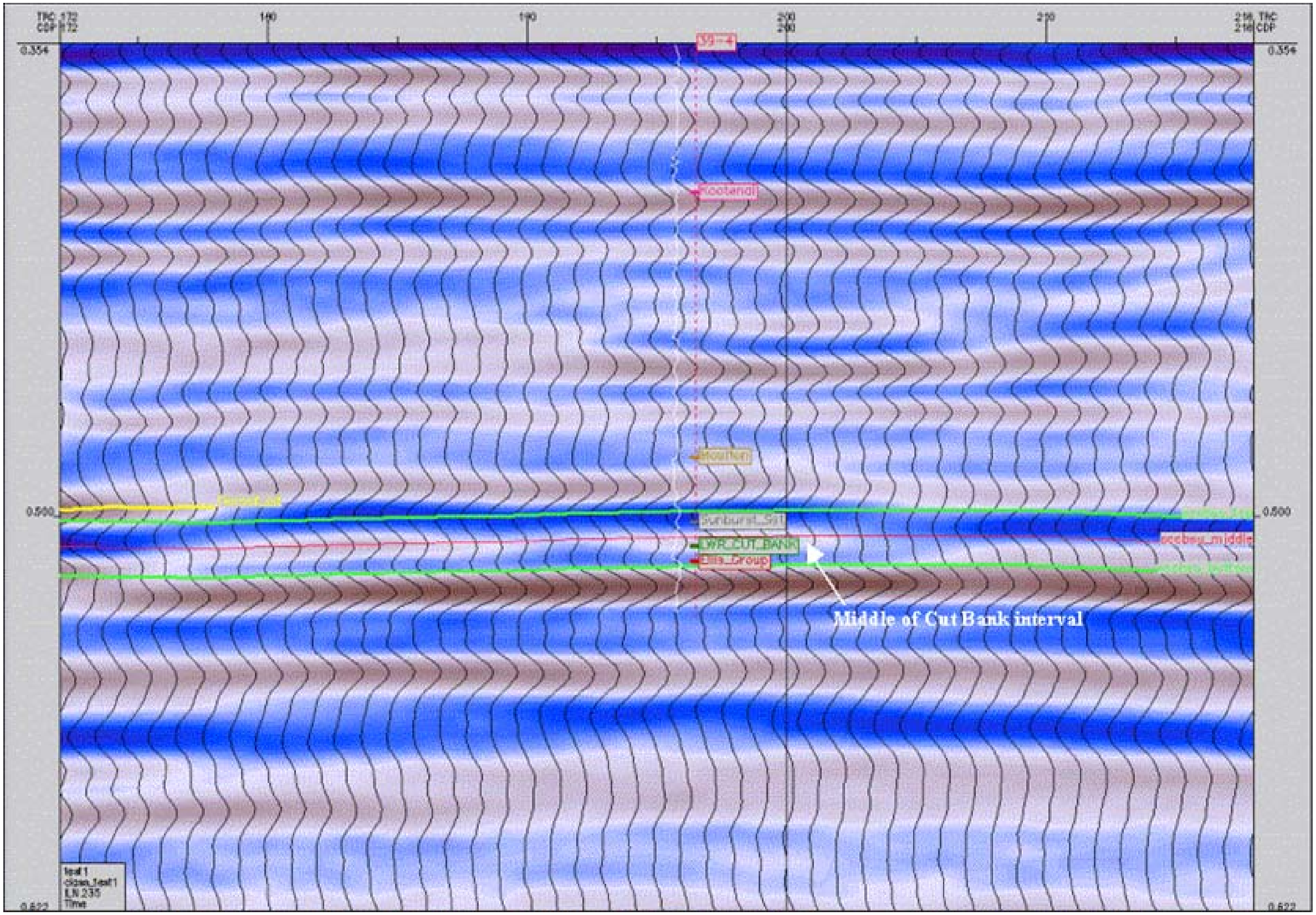


Fig. 16. Seismic section along inline 235 displaying upper, middle , and lower bounding stratal surfaces. In Well 39-4 the maximum amplitude value under-predicts the porosity. One of the reason may be inconsistency of interpretation of Lower Cut Bank interval in well log and seismic intepretation. Middle of Cut Bank interval in seismic does not correspond to the top of Lower Cut Bank interval.

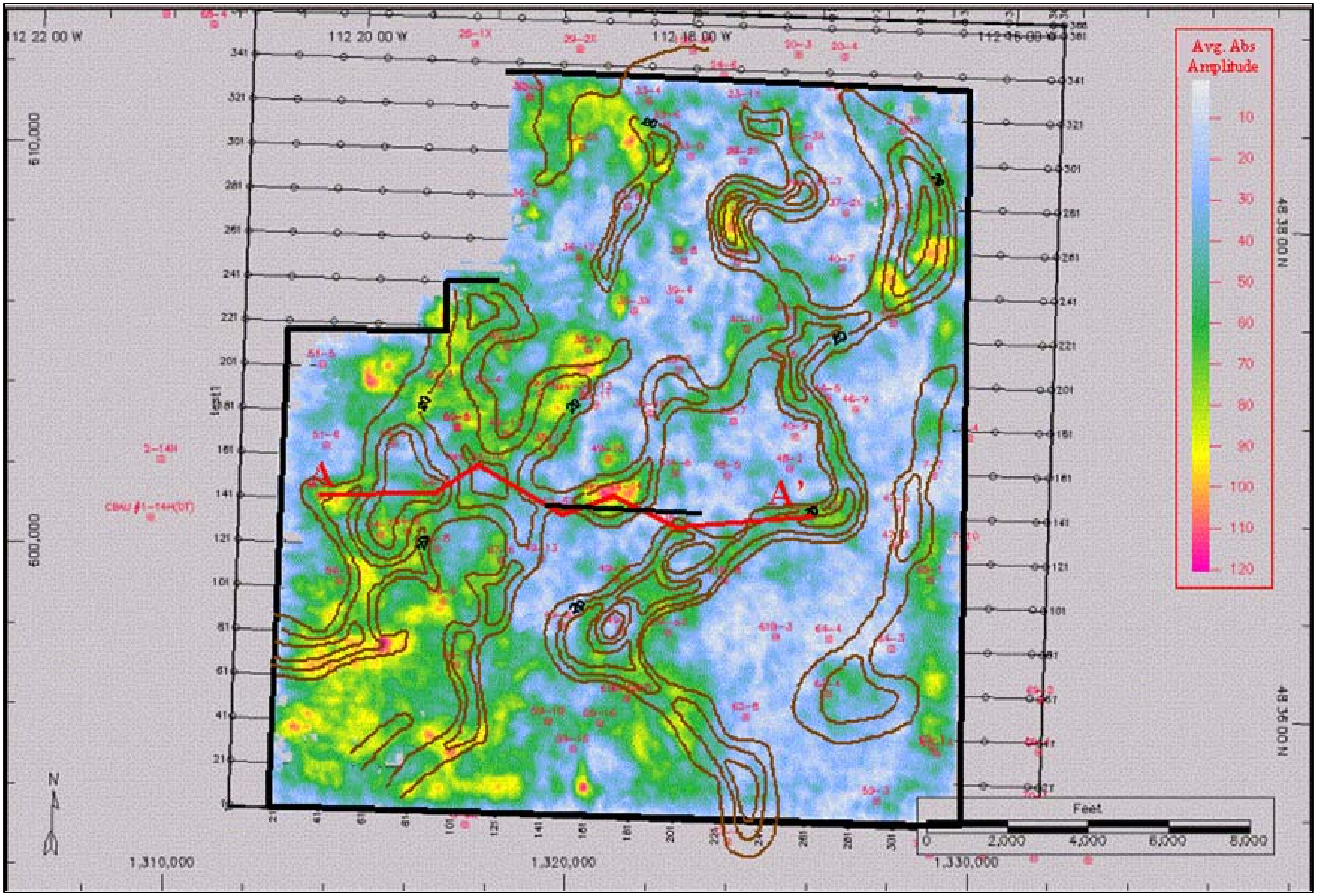


Fig. 17. QRI/BEG net sand thickness contours >15 ft superposed on the average absolute seismic amplitude map. Generally, higher average absolute amplitude corresponds to greater net sand thickness.

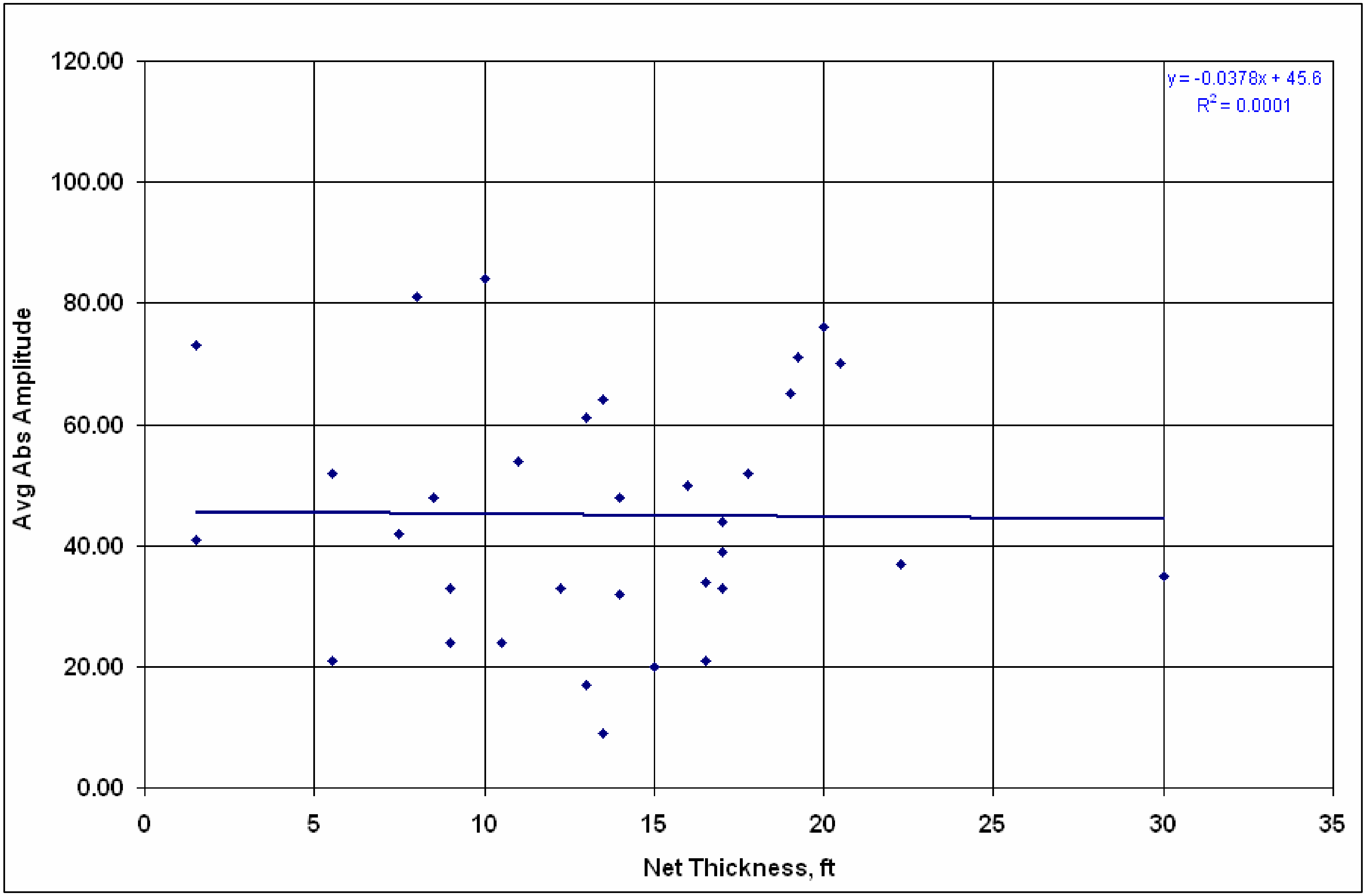


Fig.18 . There is no correlation between net sand thicknesses from well logs (based on 60% GR and 10% porosity cutoff) and average absolute seismic amplitude.

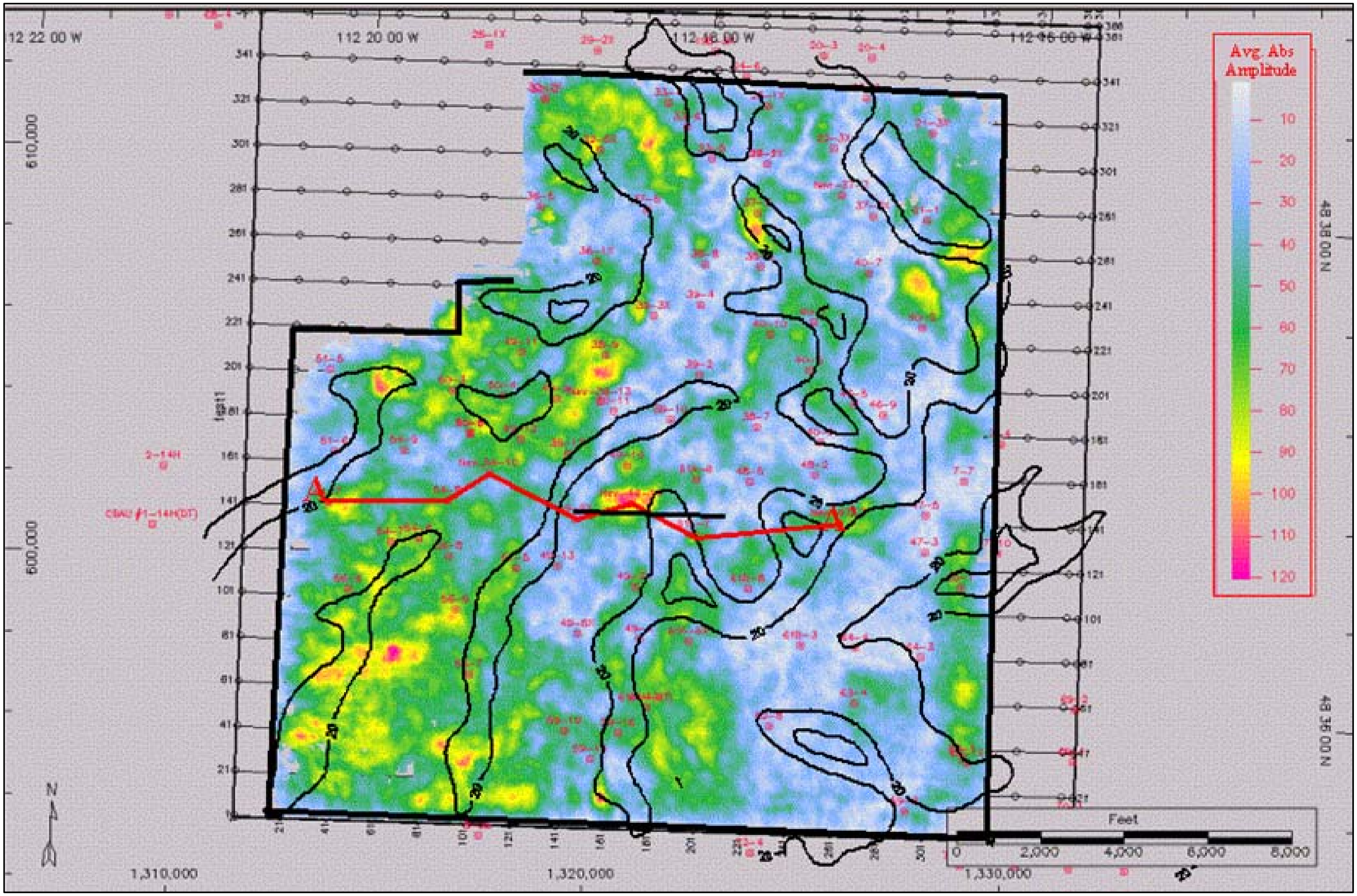


Fig. 19. UNOCAL net sand thickness contours (20 ft and greater thickness) superposed on the average absolute seismic amplitude map.

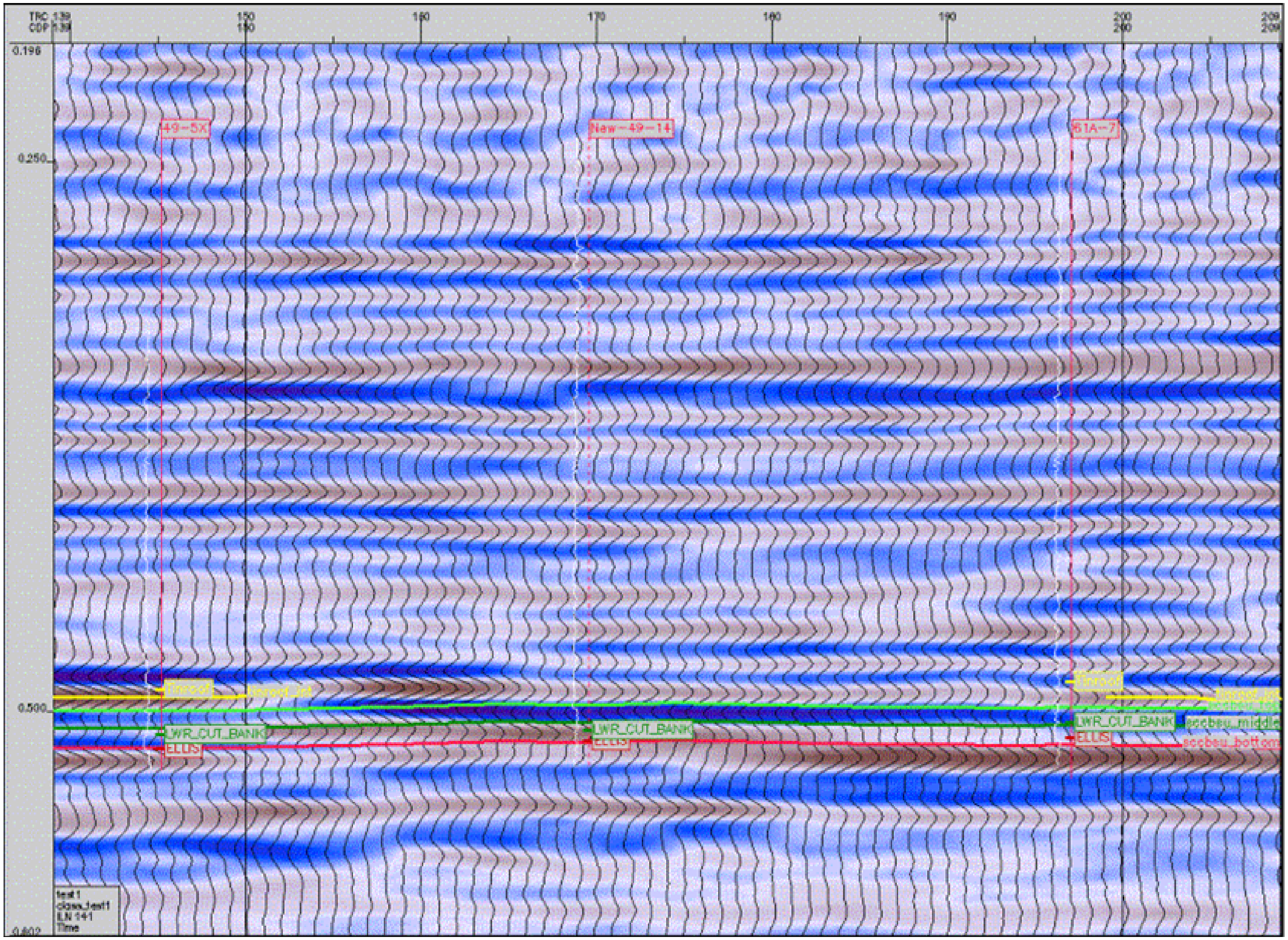


Fig. 20. West to east seismic cross-section (along inline 141) through the SCCBSU 49-14 well. Red marker is base of Cut Bank or top of Ellis; dark and light green markers are top of lower Cut Bank and top of upper Cut Bank, respectively. Location of this cross section is shown as black line in Figures 17 and 19.

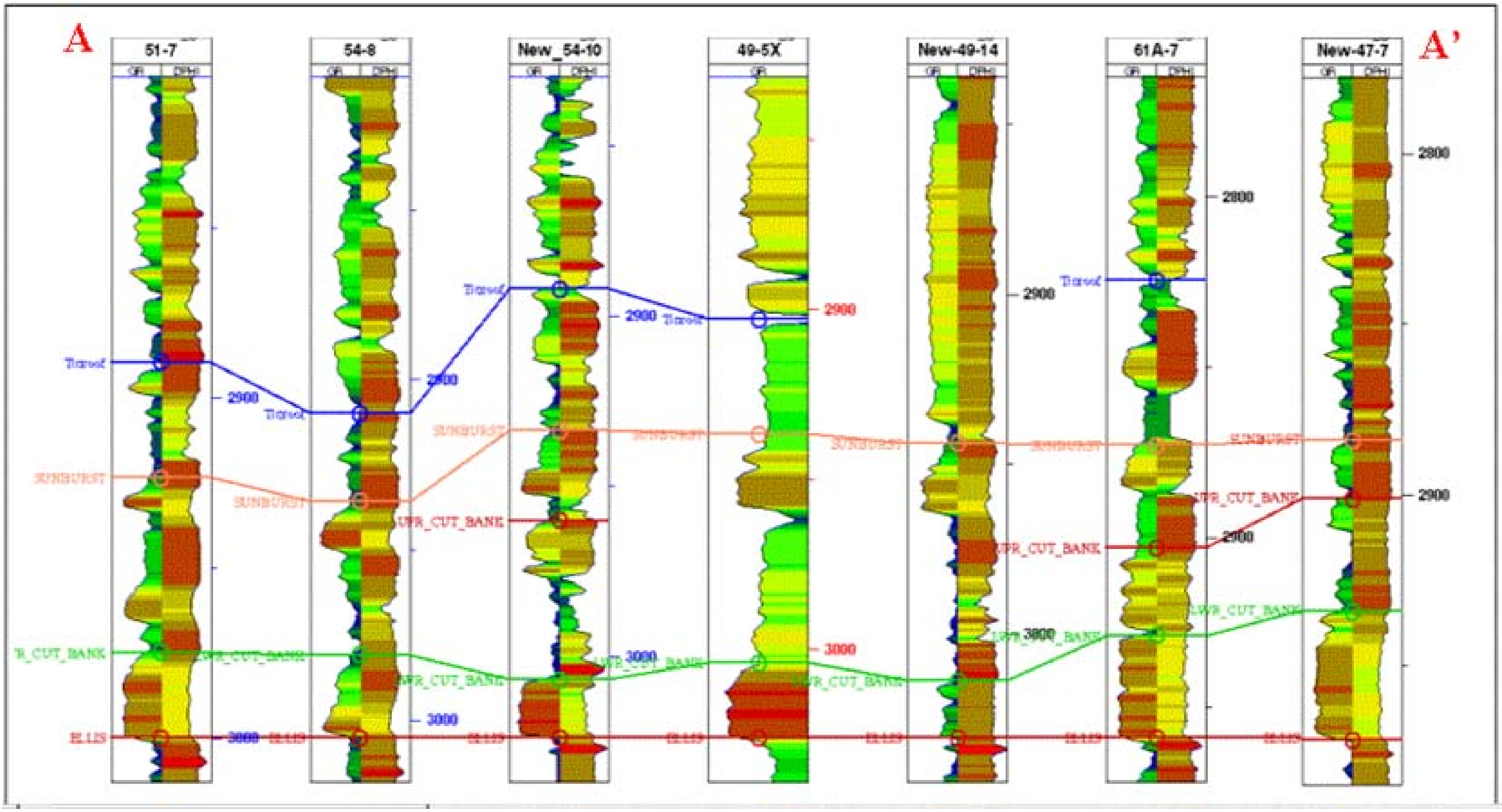


Fig. 21. East to west cross-section through the SCCBSU 49-14 well . GR scale increases from 0 to 150 API from left to right; DPHI – density porosity increases from –0.15 to 0.45 from right to left. Location of this cross section is shown as red line in figures 17 and 19.

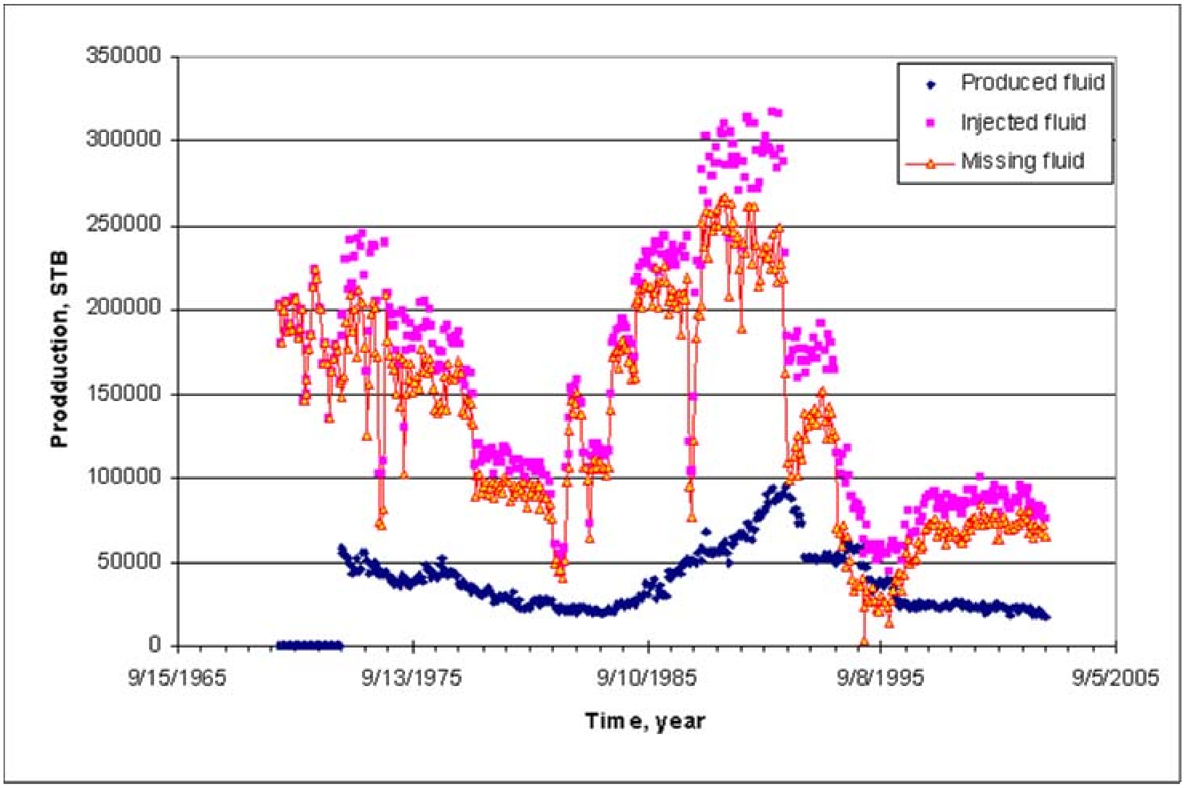


Fig. 22. History of produced fluid, injected fluid and missing fluid. Most of the injected fluid is missing in the formation of SCCBSU.

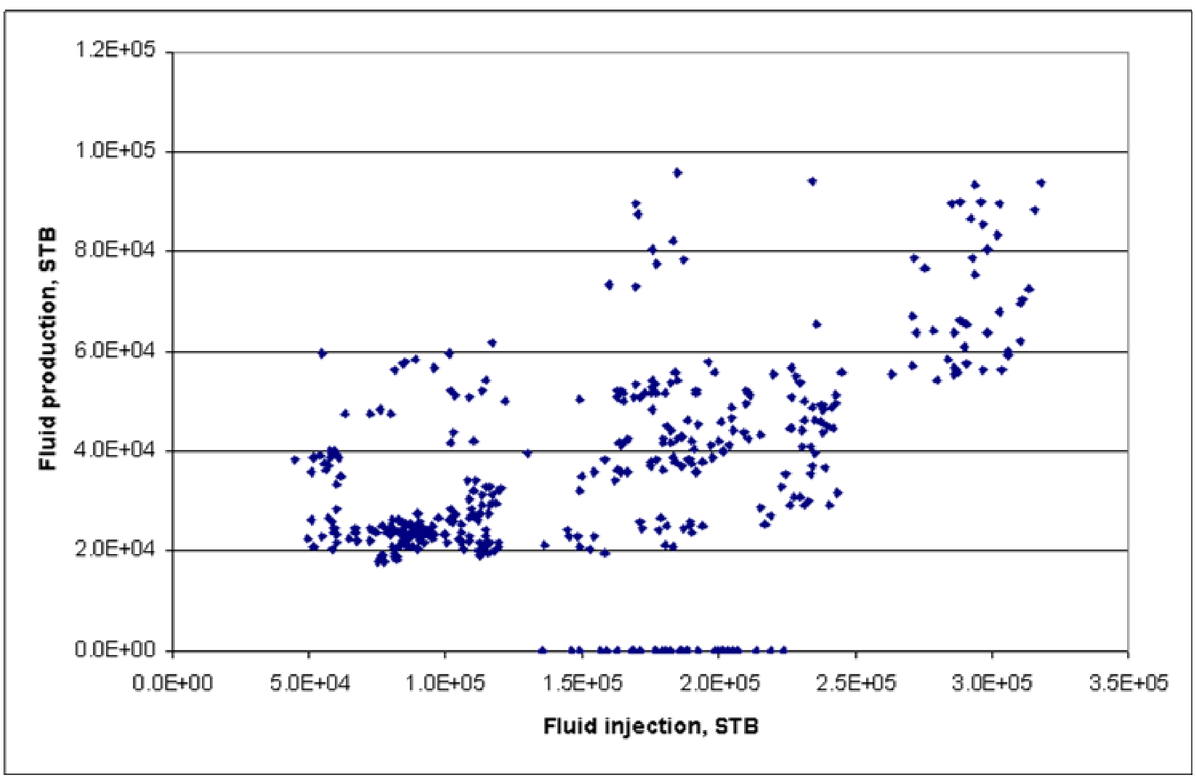


Fig. 23. Correlation between fluid injection and fluid production is not good.

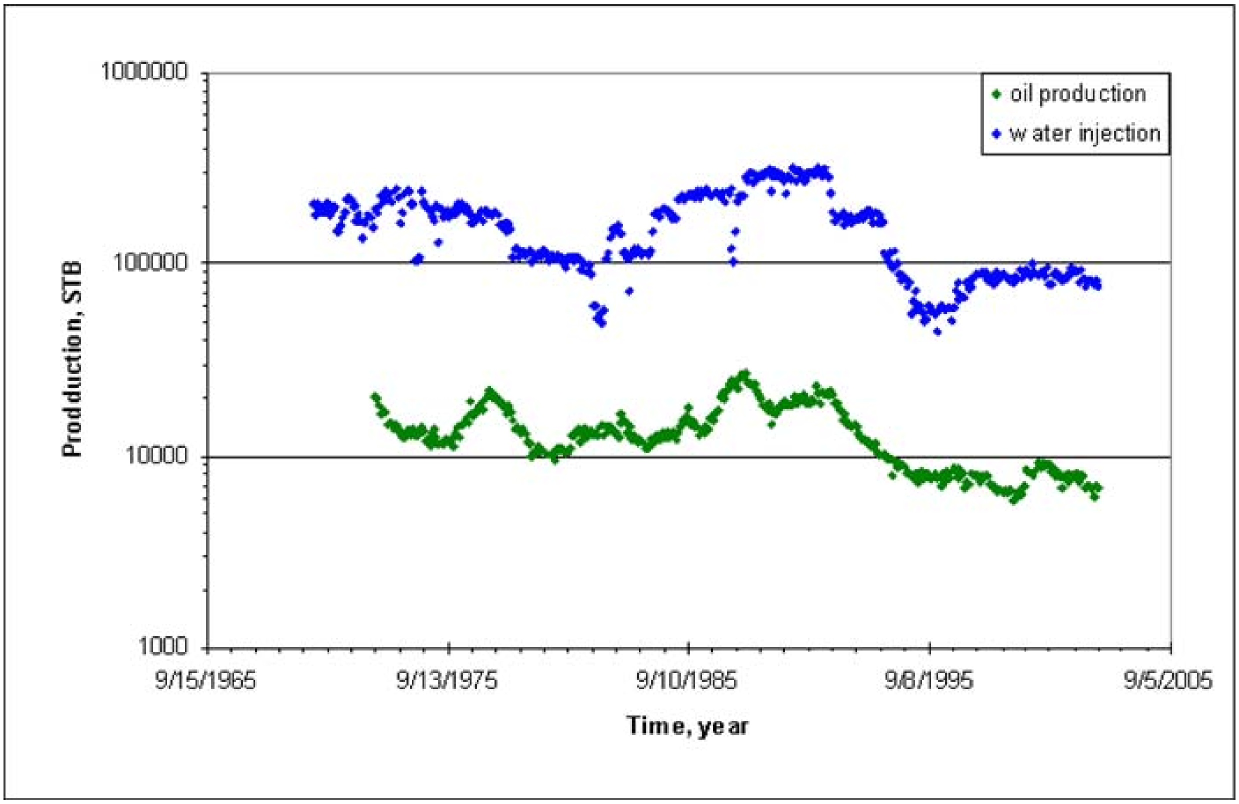


Fig. 24. SCCBSU production and injection history from year 1968 to 2002. The increase in water injection does not increase the oil production very much for the whole SCCBSU

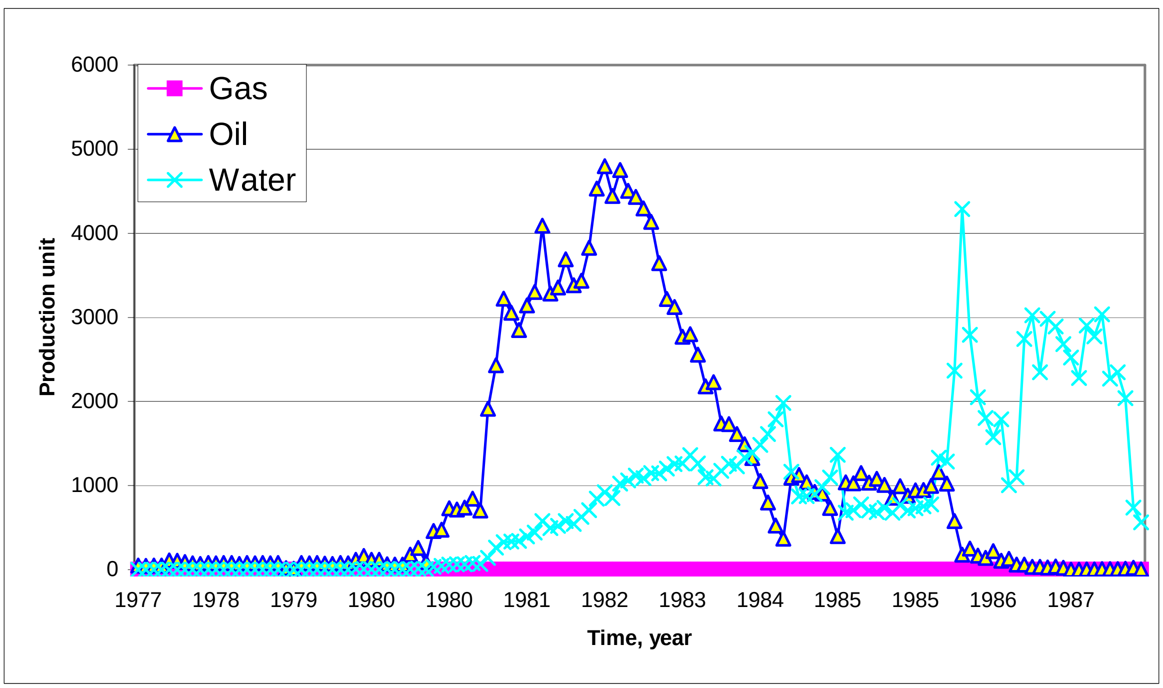


Fig. 25. Production history of well API 2503505004, showing response to water injection.

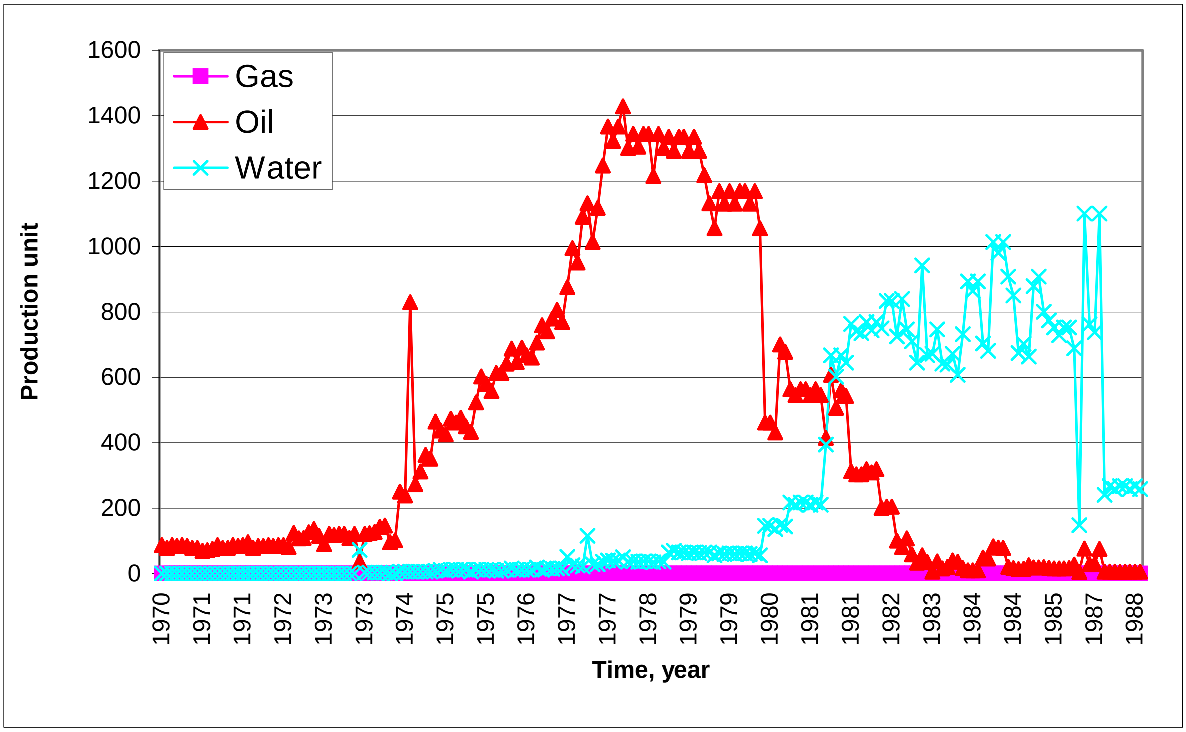


Fig. 26. Production history of well API 2503505637, showing response to water injection.

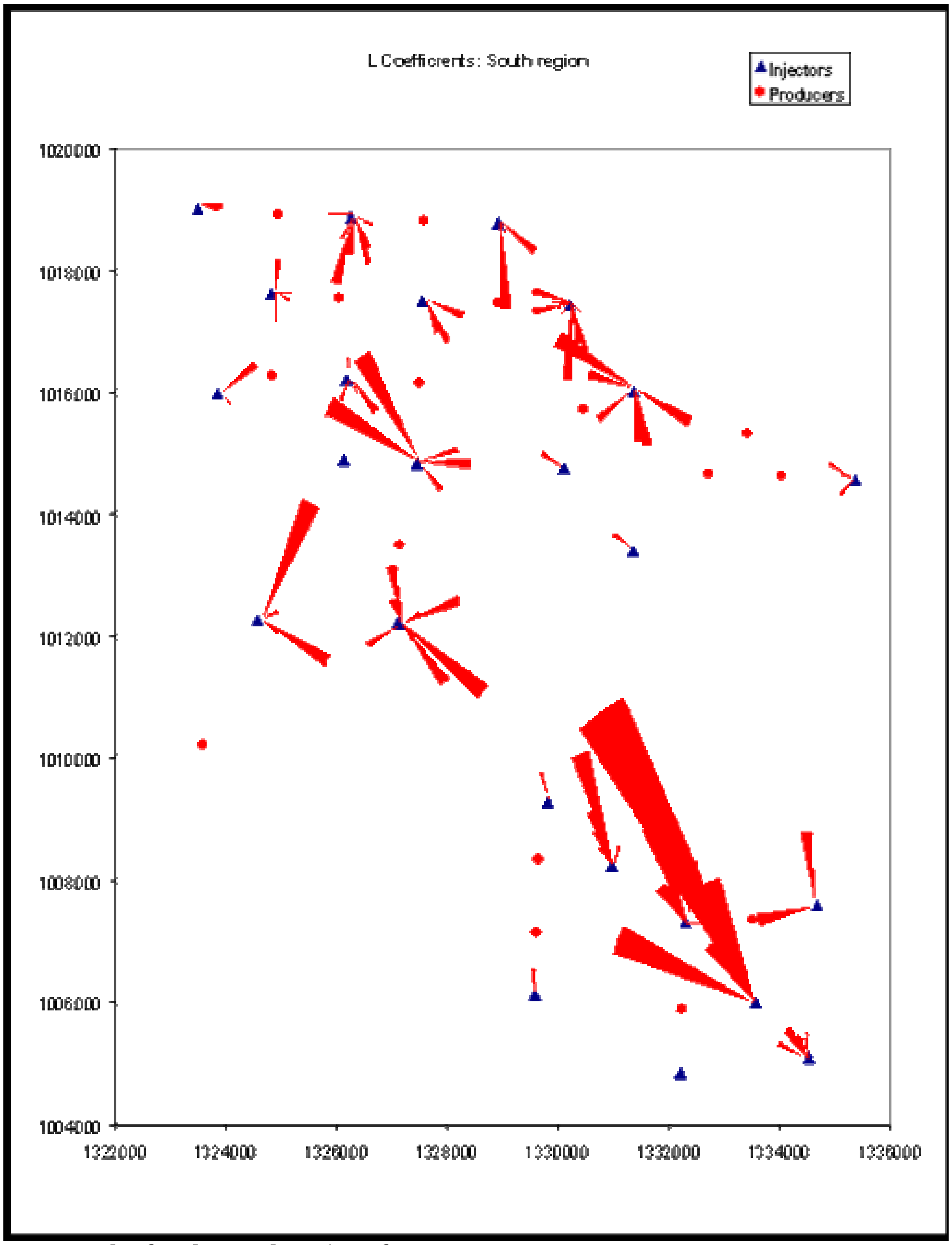


Fig. 27. Arrow plot for the south region of SCCBSU.

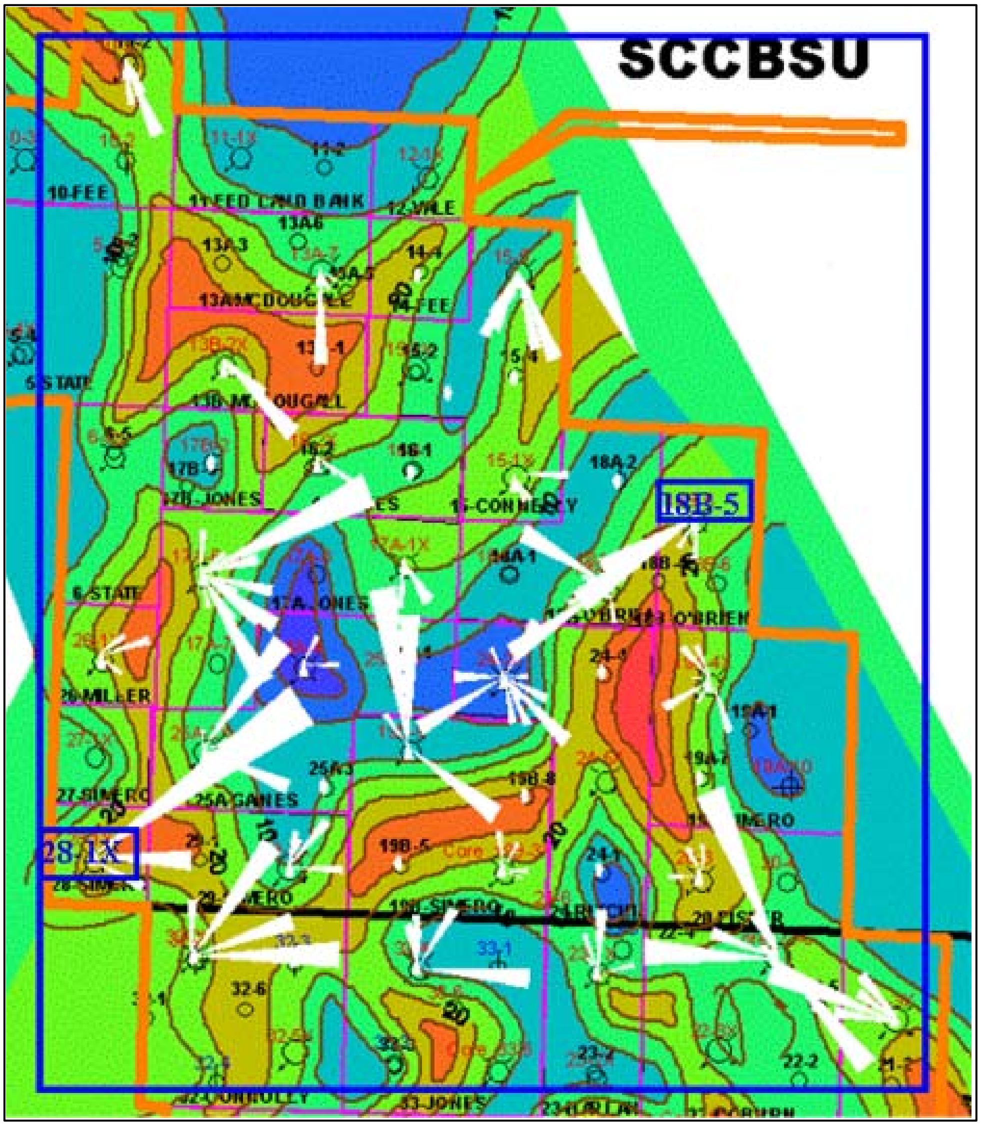


Fig. 28. North region QRI-BEG net-sand thickness map with arrow plot overlaid. Note the strong connectivity between the wells 28-1X, in the south-west area, with producer 18B-5, to the north-east.

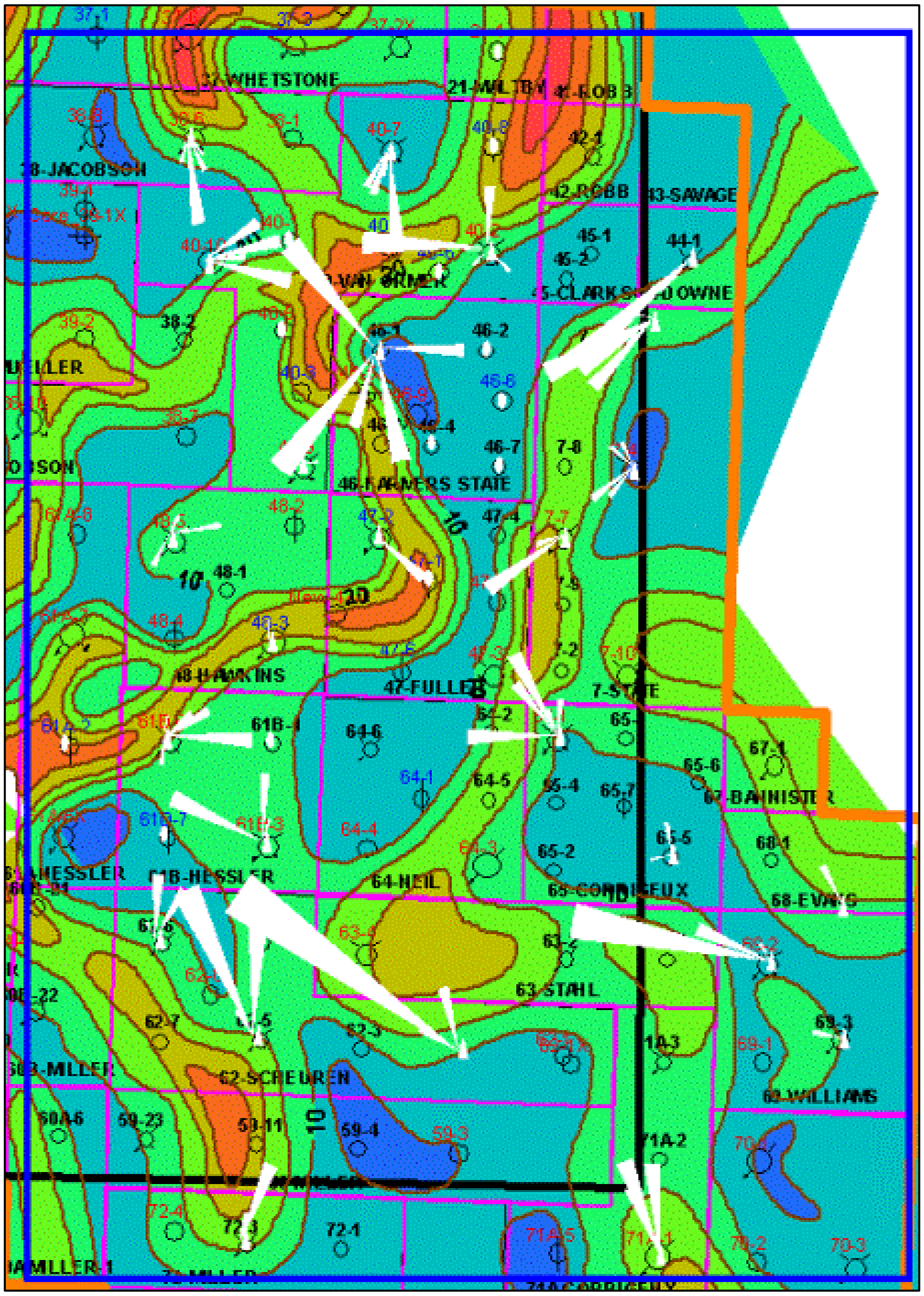


Fig. 29. North-central region QRI-BEG net-sand thickness map with arrow plot overlaid.

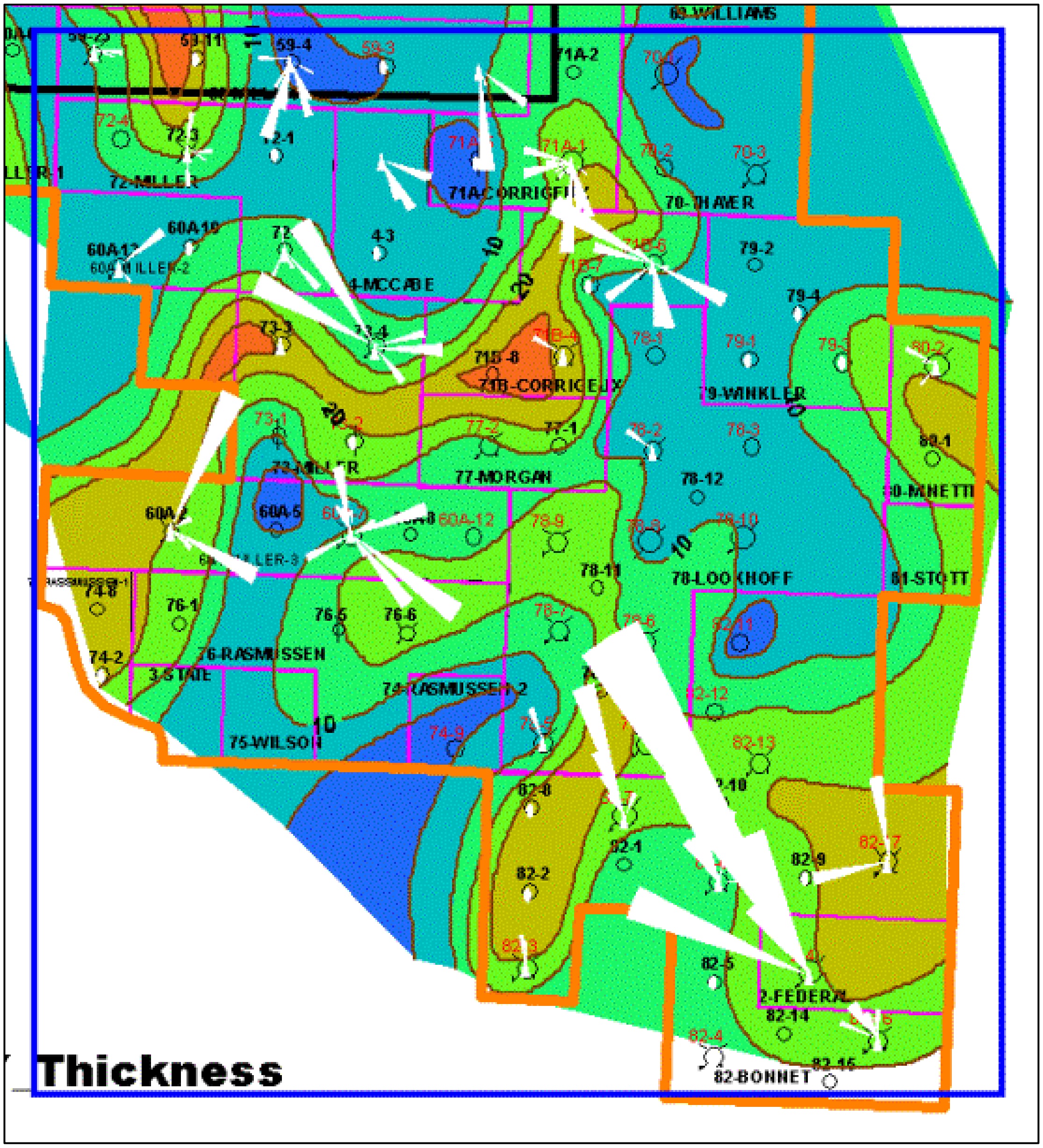


Fig. 30. South region QRI-BEG net-sand thickness map with arrow plot overlaid.

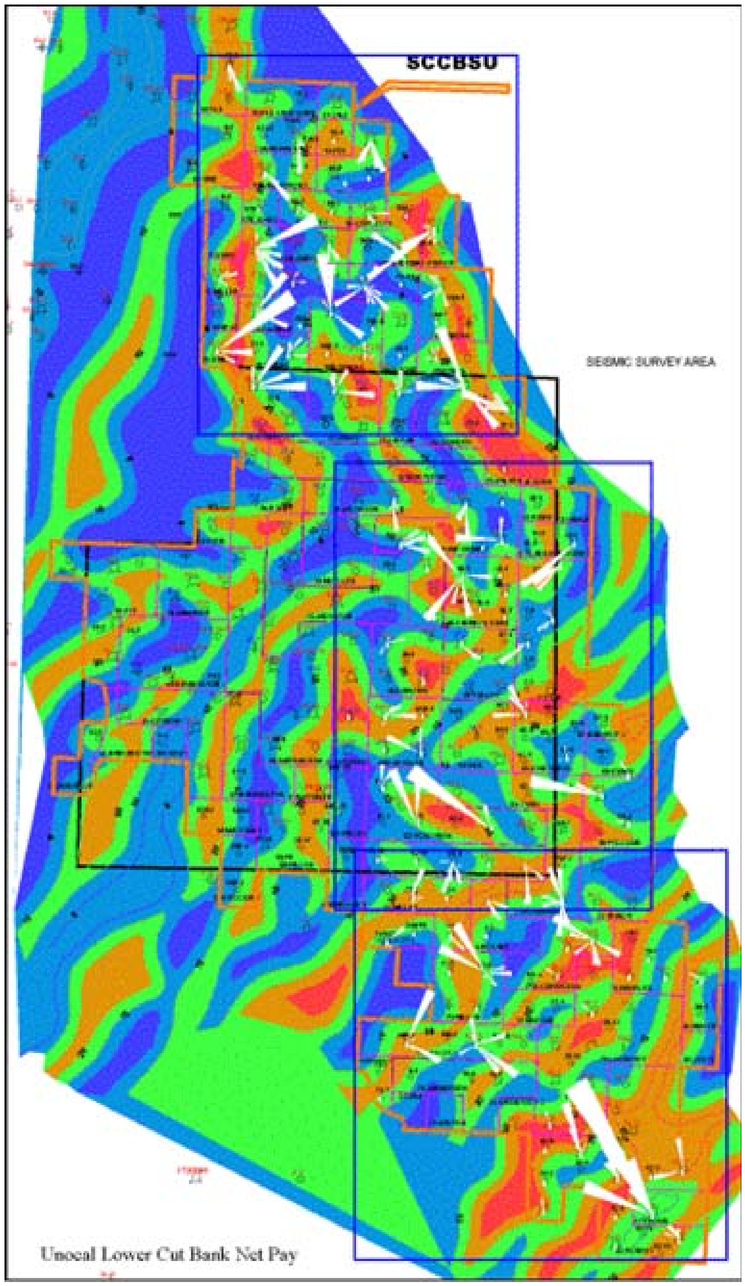


Fig. 31. SCCBSU net-thickness map (Unocal vintage) with arrow plot overlaid. Observe the poorer agreement of the arrows with net-thickness orientation compared to the net-thickness maps of Figs. 28-30.

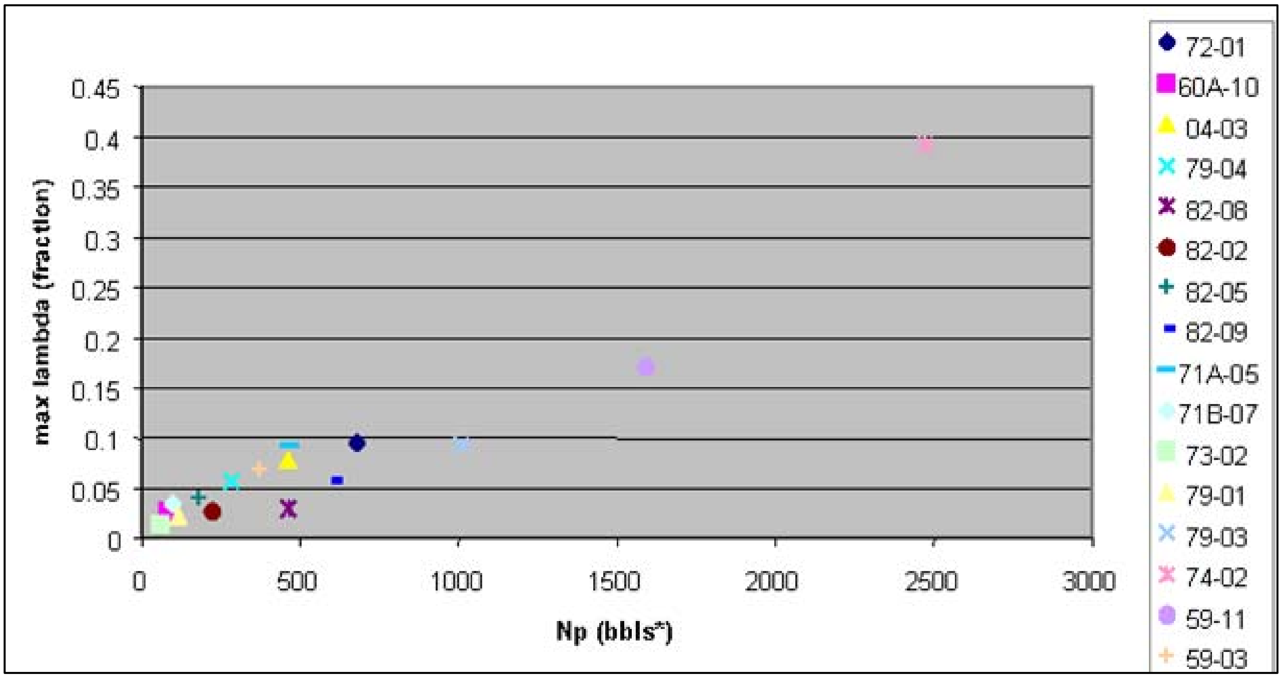


Fig. 32. Maximum λ and cumulative oil show some direct proportionality for producing wells in the South region.

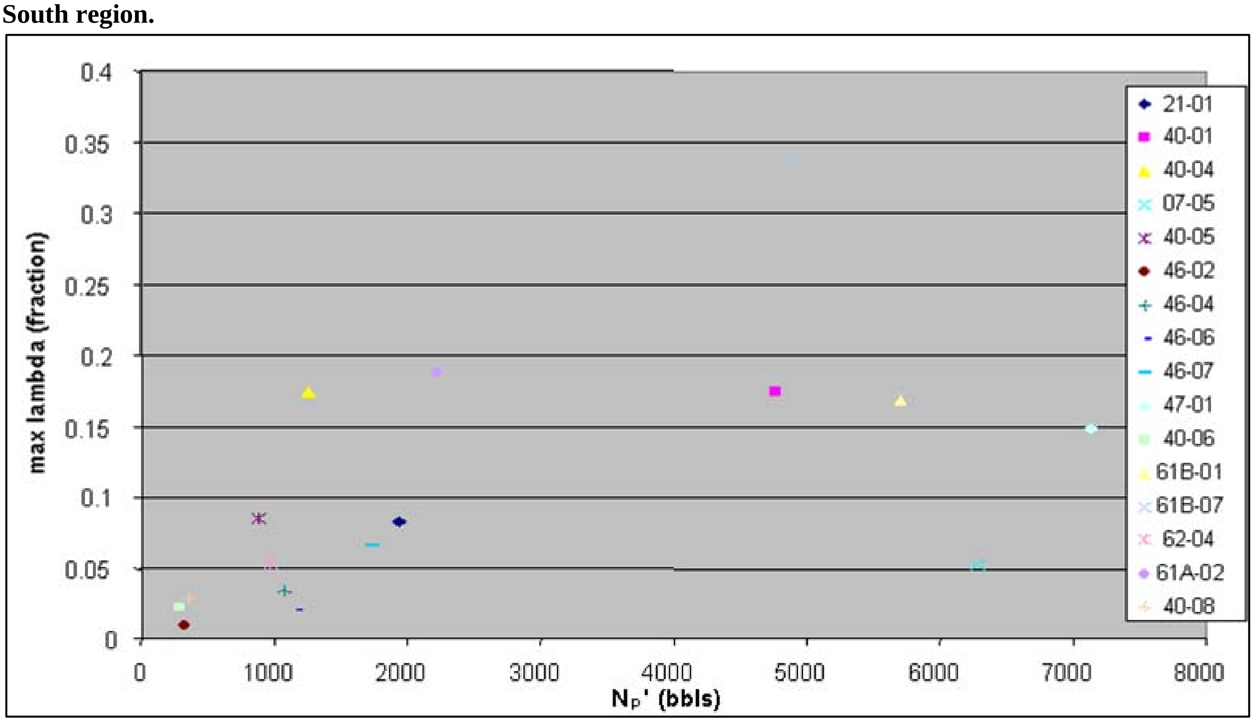


Fig. 33. Maximum λ and cumulative oil show some direct proportionality for producing wells in the North-central region.

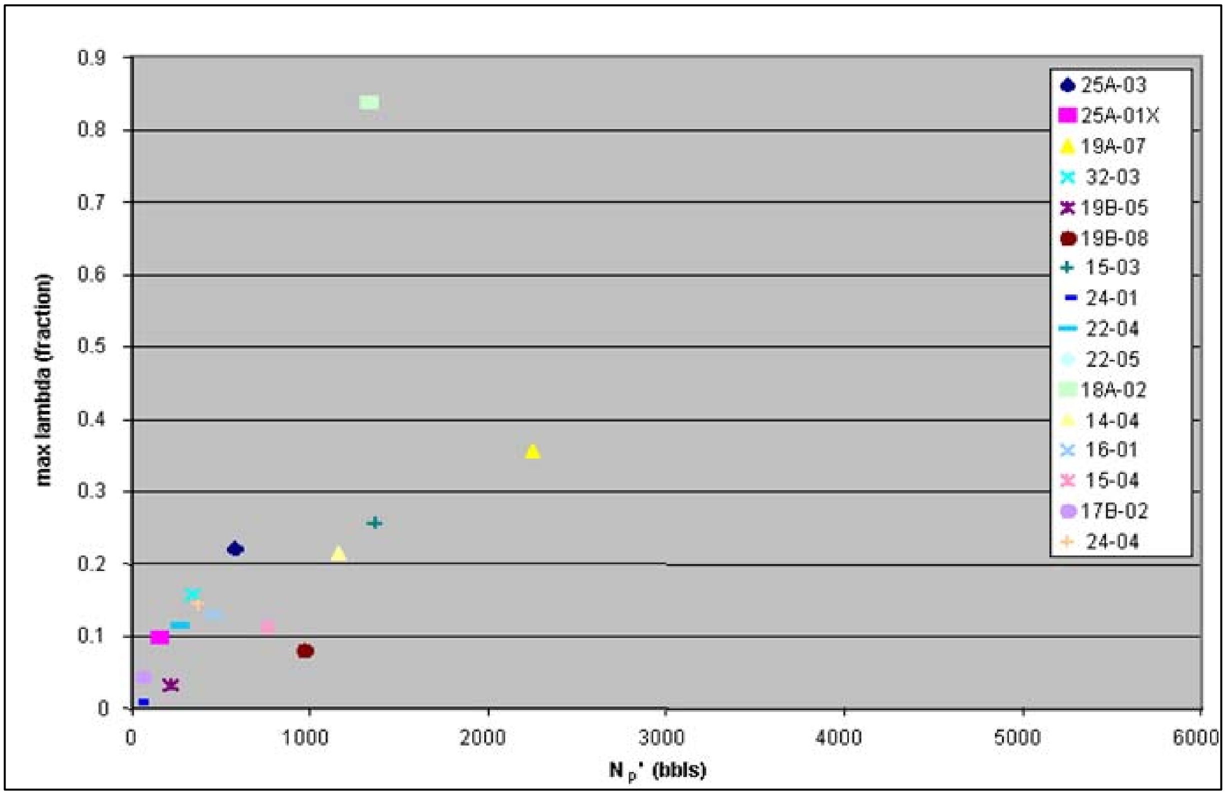


Fig. 34. Maximum λ and cumulative oil show some direct proportionality for producing wells in the north region.

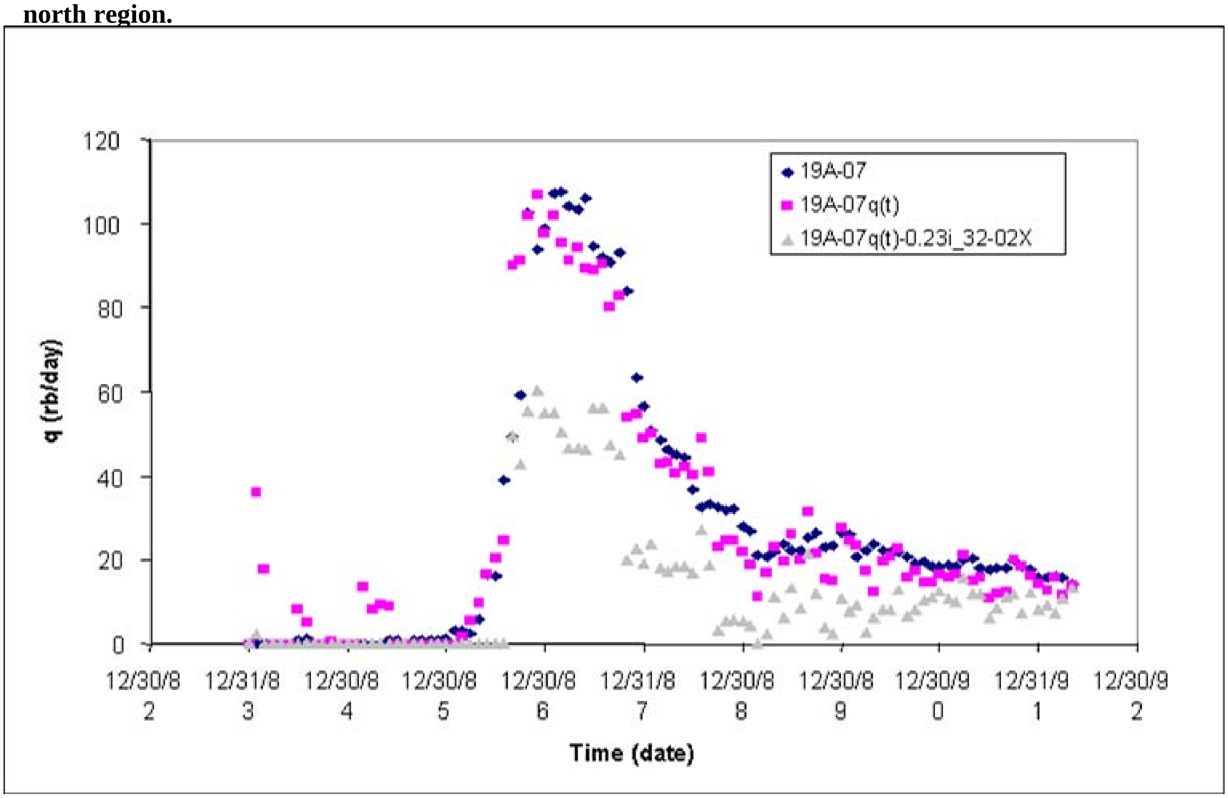


Fig. 35. North region – actual (blue diamonds) and predicted (red boxes) production from well 19A-07. Eexclusion of the contribution of injector 32-02X from the production of well 19A-07 (grey triangles) results in a large discrepancy with the calculated production

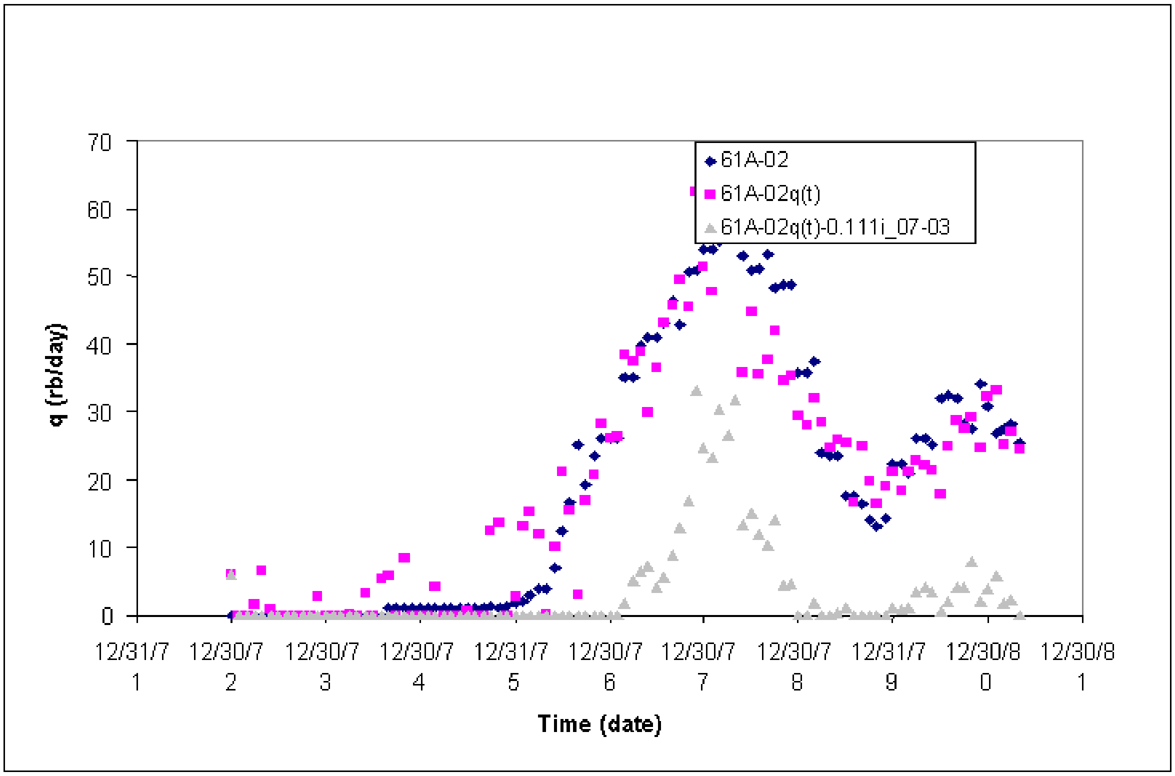


Fig. 36. North-central region –actual (blue diamonds) and predicted (red boxes) production from well 61A-02. Exclusion of the contribution of injector 07-03 from the production of well 61A-02 (grey triangles) results in a large discrepancy with the calculated production.

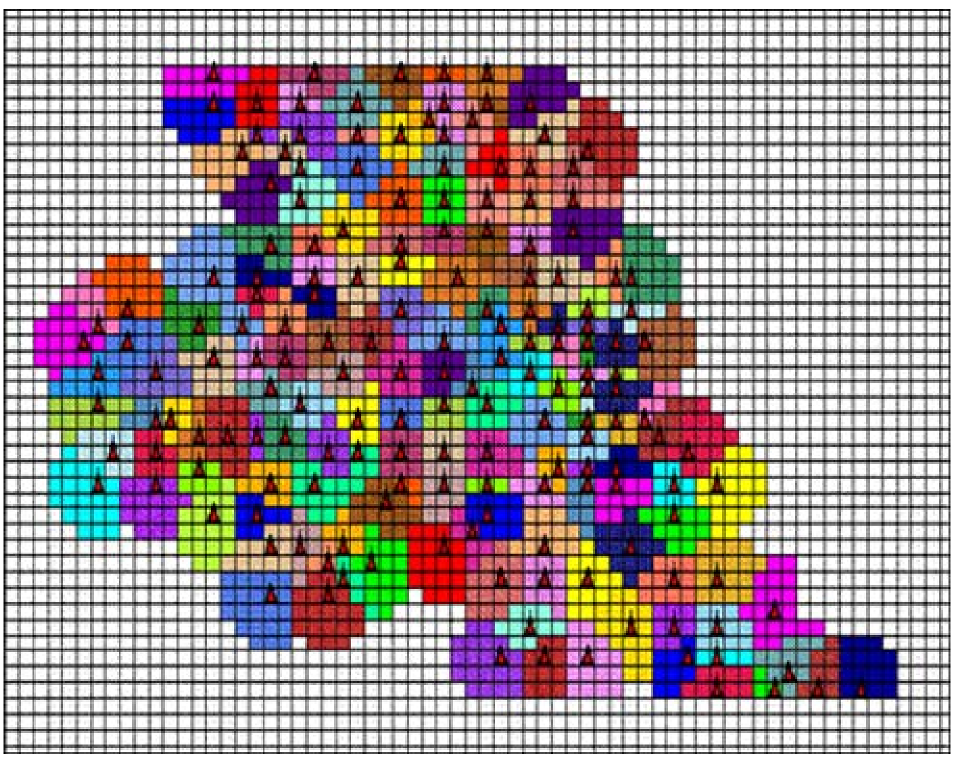


Fig. 37 Permeability regions depicted around each individual well.

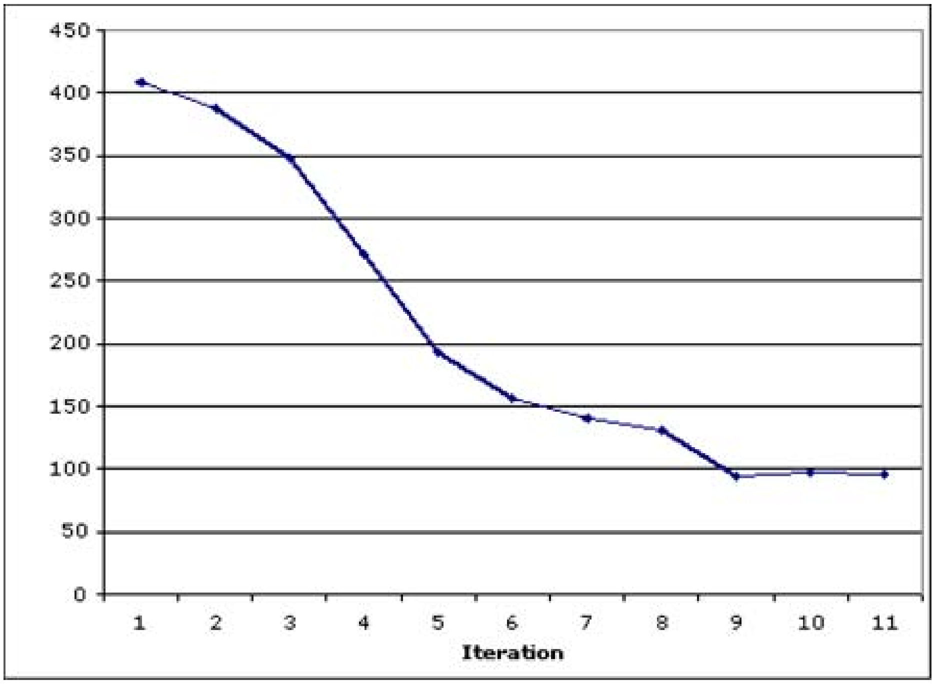
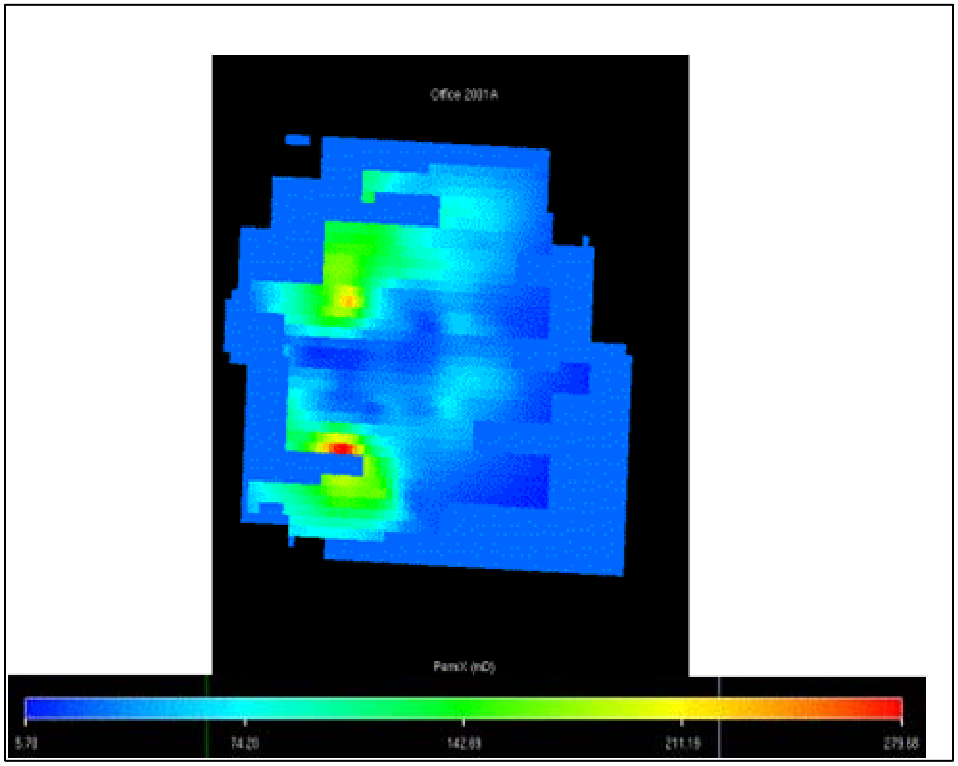


Fig. 38 Regression performance. Convergence obtained after 9 iterations.



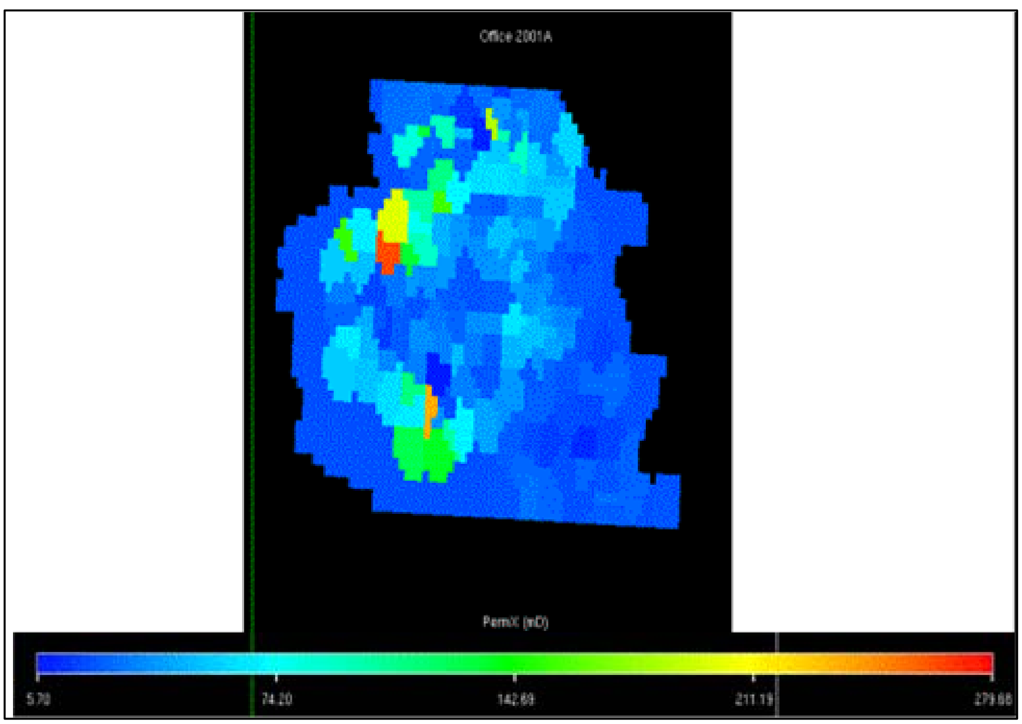


Fig. 39 - Comparison of permeability maps. To the top (a) is the map used to generate the observed production data and to the bottom (b) is the map obtained after the regression.

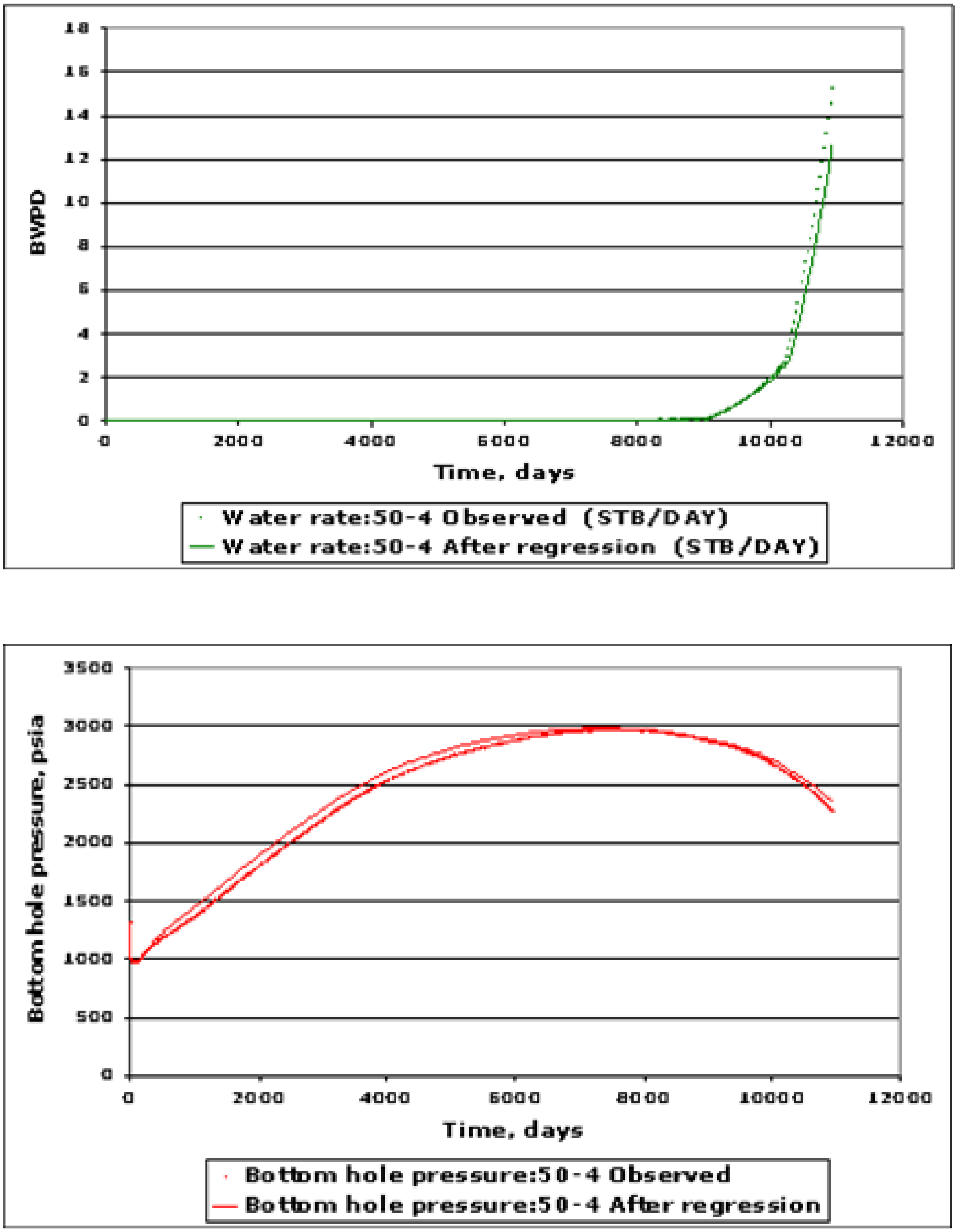
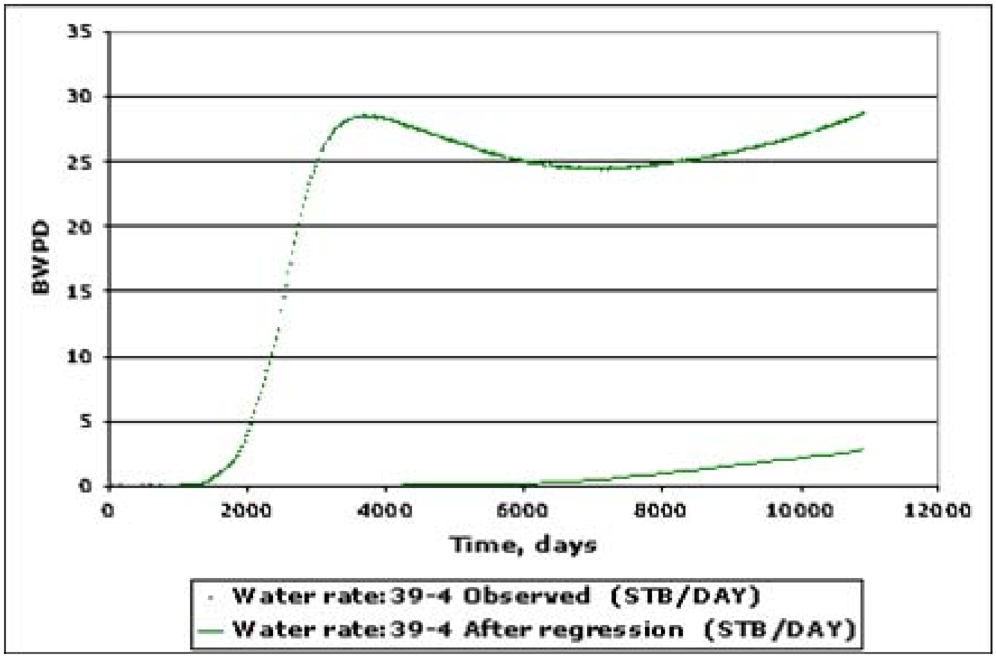


Fig. 40 - Best matched well for water production (top) and pressure (bottom) after the regression.



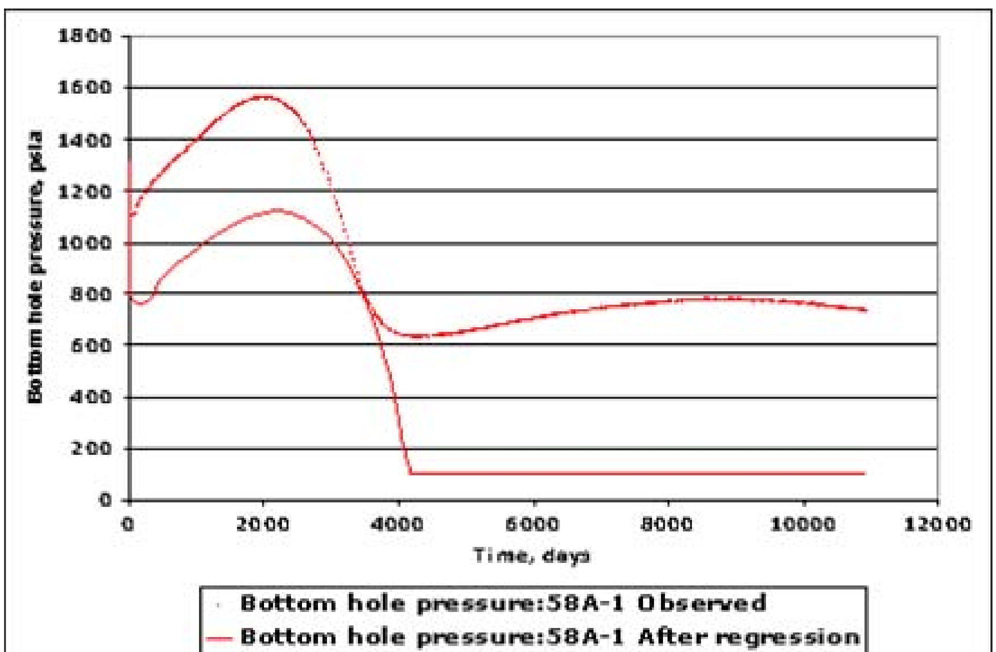


Fig. 41 - Worst matched well for water production (top) and pressure (bottom) after the regression.

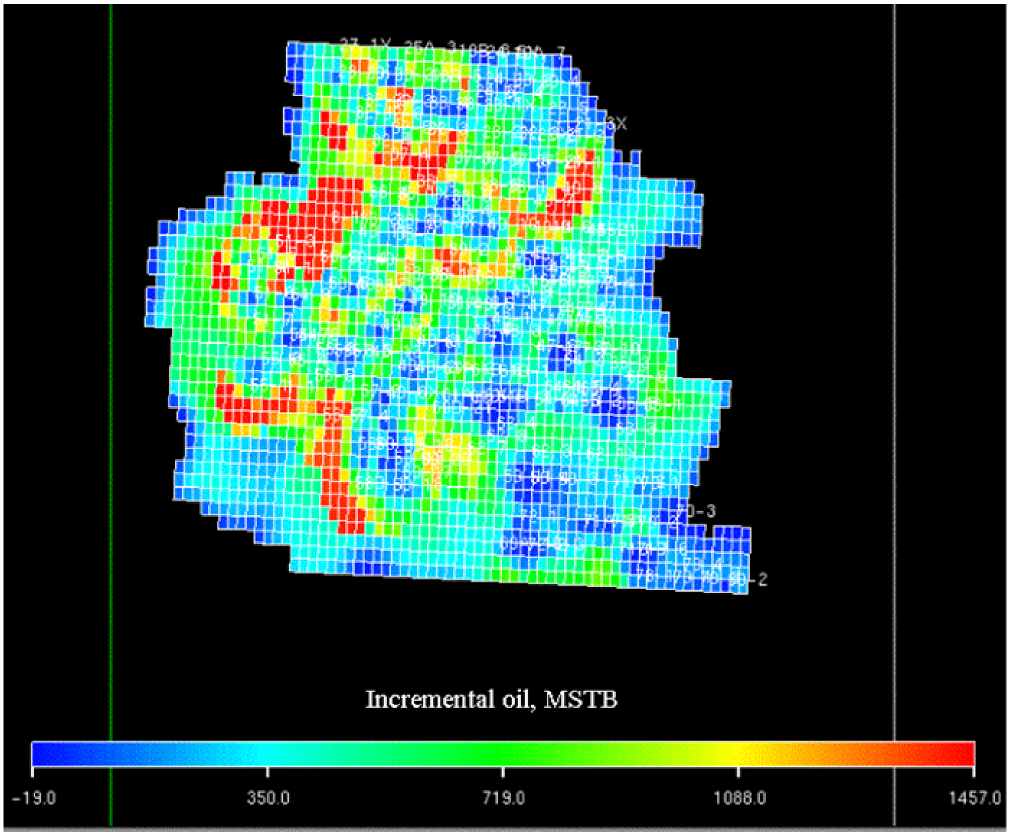


Fig. 42 - Infill incremental oil recovery with regressed permeability field, synthetic case.

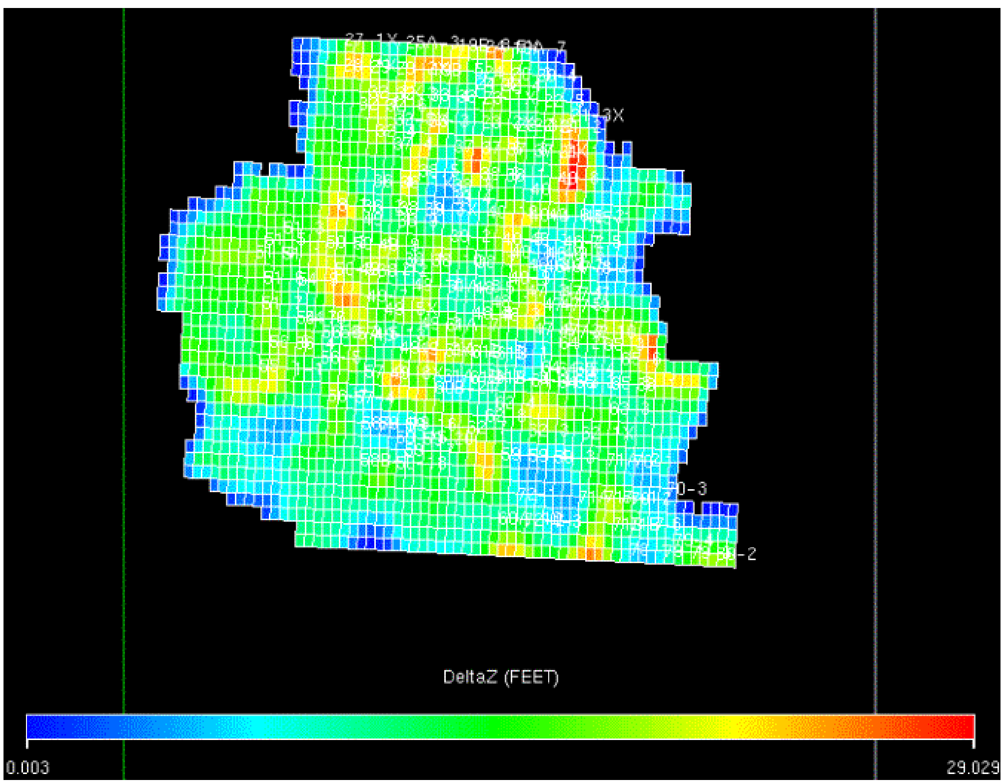


Fig. 43 - Net pay map.

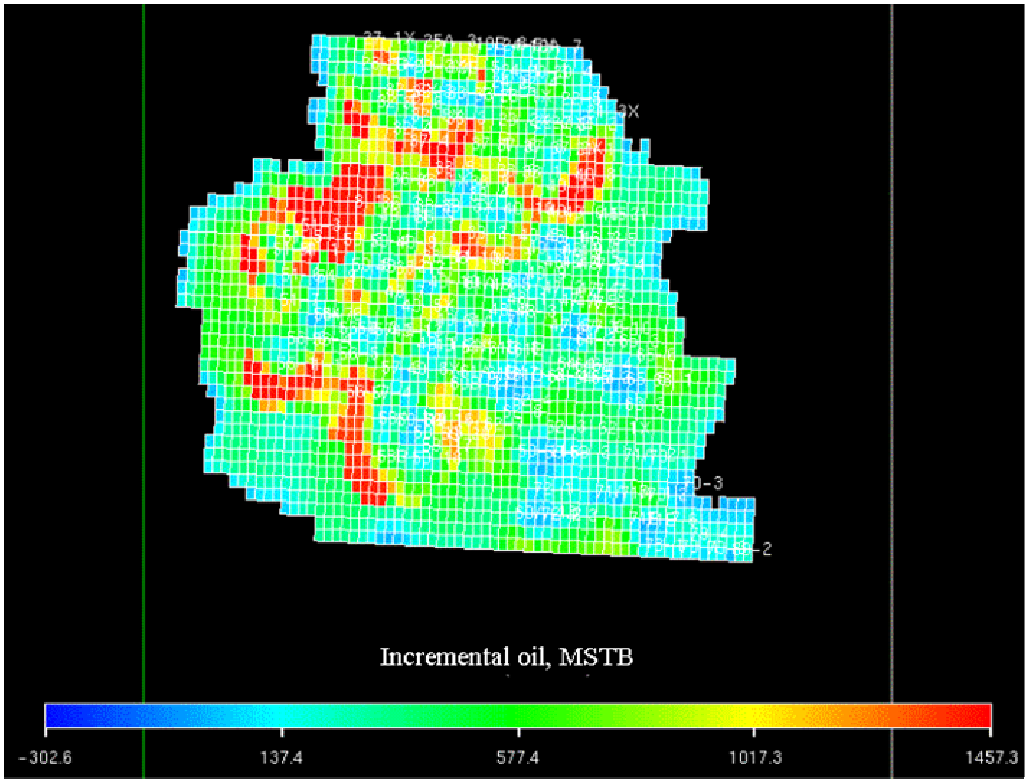


Fig. 44 - Infill incremental oil recovery with known permeability field, synthetic case.

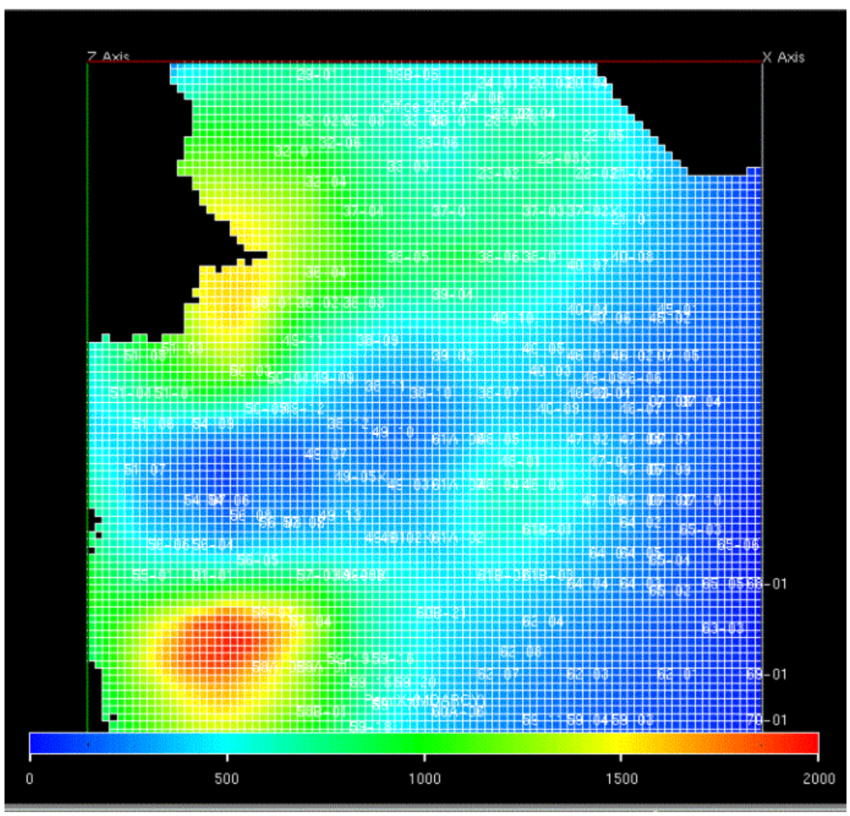


Fig. 45 - Permeability map for actual case prior to regression.

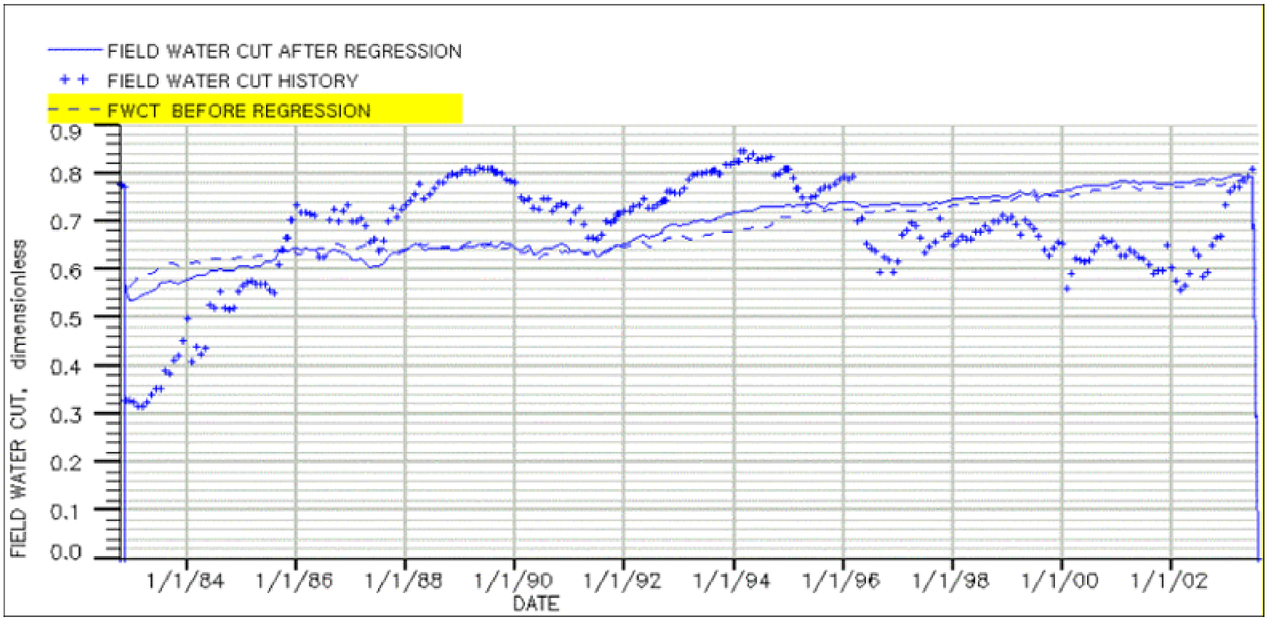


Fig. 46 - Match of field water cut for the actual case, after fieldwide matching but prior to individual well regression.

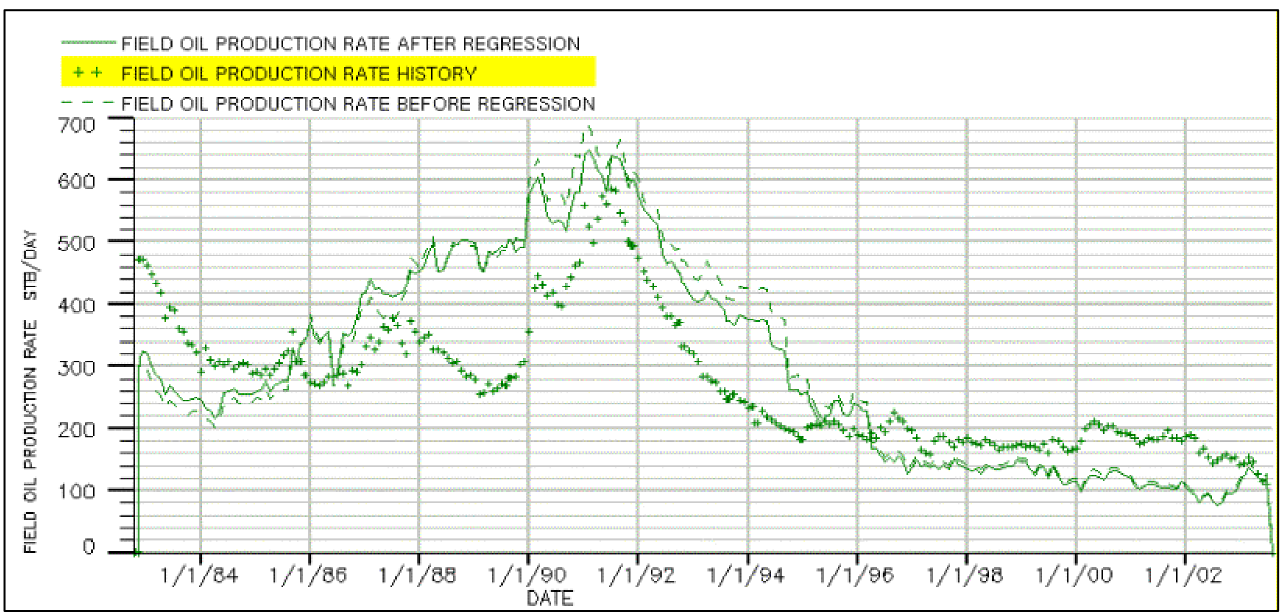


Fig. 47 - Match of field oil production rate for the actual case, after fieldwide matching but prior to individual well regression.

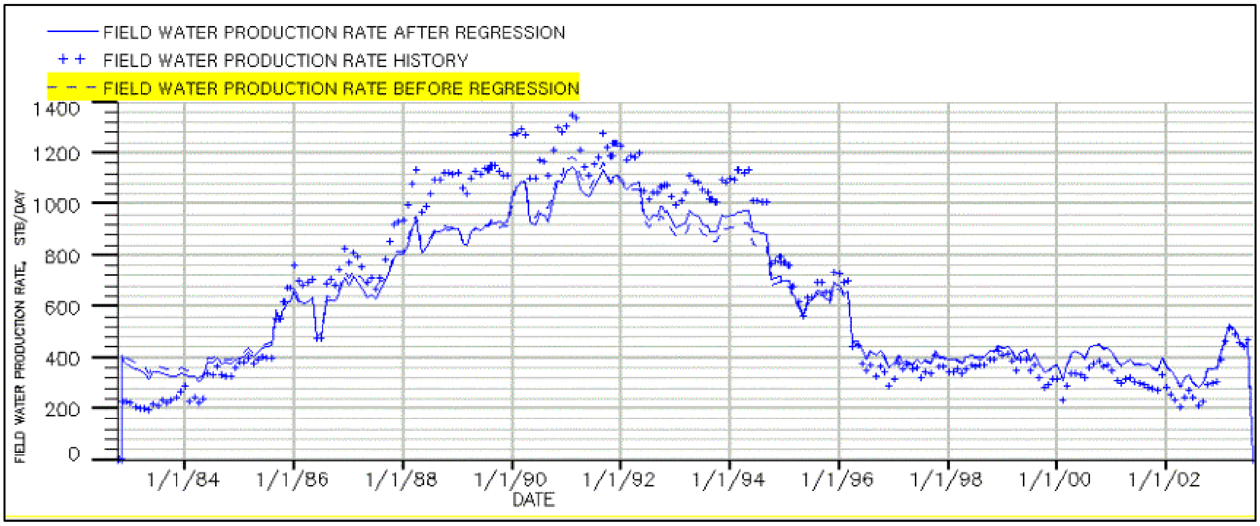


Fig. 48 - Match of field water production rate for the actual case, after fieldwide matching but prior to individual well regression.

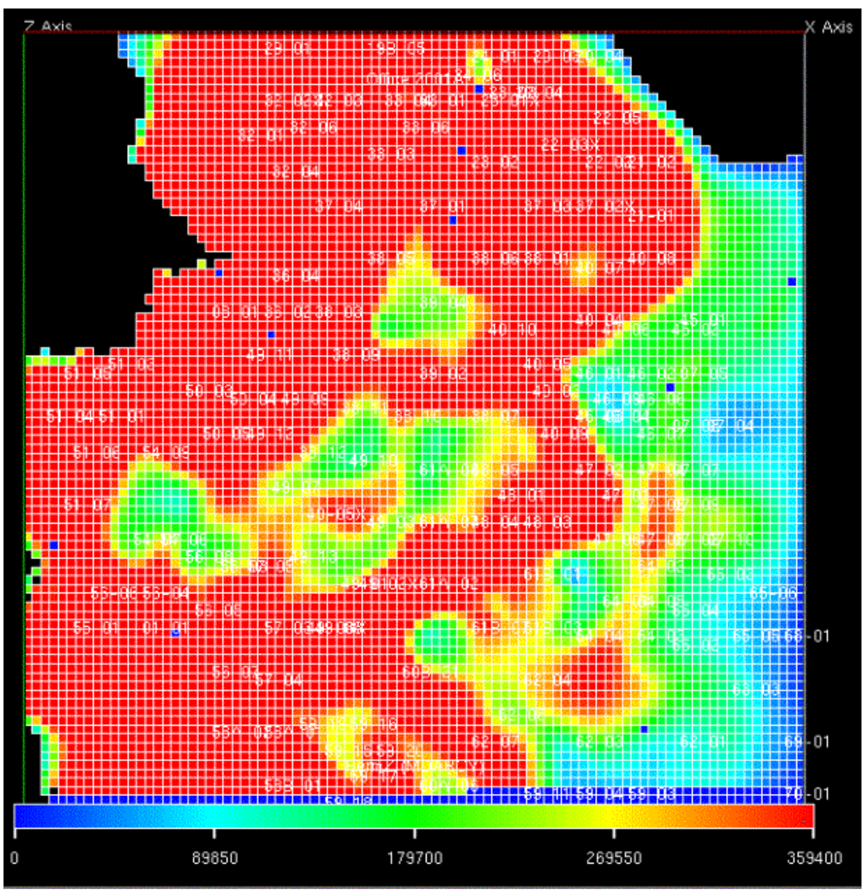


Fig. 49 - Map of infill incremental oil recovery for the actual case.